AFIT/GTM/LAL/99S-3

LOGISTIC REGRESSION MODELING OF DIMINISHING MANUFACTURING SOURCES FOR INTEGRATED CIRCUITS

THESIS

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THESIS

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Michael J. Gravier

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Abstract

The problem of Diminishing Manufacturing Sources and Material Shortages (DMSMS) afflicts the Air Force in a way unforeseen in the past. Integrated circuits are especially hard hit. The costs of DMSMS manifest both in terms of monetary expense and diminished mission readiness. The current environment of limited defense spending and high operations tempo exacerbates this problem. This thesis draws on data from available electronics databases to assess whether statistical modeling offers a viable method for predicting the presence of DMSMS. Logistic regression was used for analysis of DMSMS and used to develop twenty models to identify the "best" way to model and predict DMSMS. The results indicated that DMSMS does not seem related to technical characteristics. However, design age proved statistically significant in modeling DMSMS presence. This research also indicated that integrated circuits designed for military use have extended longevity compared to commercial integrated circuits.

The overall conclusion of this effort was that DMSMS can be predicted without much difficulty using the conditional probability output of logistic regression. Current databases do not provide easy access to the vital predictor, design age. Recommendations include further validation of the model and the inclusion of design age in electronics integrated circuit databases.

LOGISTIC REGRESSION MODELING OF DIMINISHING MANUFACTURING SOURCES FOR INTEGRATED CIRCUITS

I. Introduction

Statement of Problem

This thesis presents an exploratory study into creating a model relating Diminishing Manufacturing Sources and Materials Shortages (DMSMS) factors to parts availability. Stratified samples of integrated circuits will be used. Data and availability status will be drawn from IHS Engineering Products' TDMPlus group of databases in order to analyze various component characteristics. The goal is to create a statistics-based model with applicability to predicting parts availability.

According to Air Force Materiel Command's *Case Resolution Guide* (DMS Program Office, 1998: 9), DMSMS is "...the loss or impending loss of manufacturers or suppliers of items or raw materials." The importance of DMSMS cannot be overemphasized. Too few manufacturers or suppliers mean a limited capacity to repair and maintain essential Air Force assets. The increasingly common problem of no manufacturers for a particular component not only leads to potential planning disruptions, but can also increase costs dramatically.

The impact of DMSMS has proven particularly burdensome since the end of the Cold War because of several factors. Decreased military spending seems an obvious precursor to a diminished manufacturing base. Concurrent with the decreased military spending has been the ever-increasing pace of technological turnover. Electronic components experience significant improvements more frequently now than at any time in the past. Additionally, the commercial electronics industry is booming, to the point that industry no longer makes significant money in the defense sector. At the same time, the military has maintained the same technological requirements, and continues to demand outdated electronics technology for older systems.

However, not all components seem to suffer the problem of DMSMS. Some components have not changed in 20 years, while others go out of production in less than a year. The questions from the perspective of managing use of these parts are several, and have the potential to save the Air Force large sums of money and lost time. The principle questions are:

- Is there a pattern to the characteristics of DMS afflicted versus non-afflicted parts?
- What characteristics form this pattern?
- How much does each of these characteristics affect obsolescence?
- Can we use this discernible pattern (if there is one) to make predictions about the degree of DMS afflicting a part?
- Do current databases provide sufficient information to make predictions on DMS prevalence?
- How applicable is this research in the event a new technology becomes available?

Scope of Research

Obsolescence and DMSMS are multifunctional problems afflicting acquisition, procurement, manufacturing, planning, maintenance, and operations. As such, the best solution will probably involve all these functions. Such a massive coordination effort has yet to be undertaken.

Because DMSMS is relatively unstudied and its solutions relatively untried, any research which attempts to establish a measurable relationship between component characteristics and lack of availability adds potentially useful information for predicting, monitoring, and resolving DMSMS problems.

Issues, Needs, and Limitations

A prerequisite to comprehending the far-reaching ramifications of DMSMS on Air Force systems is a realization of the extent of technology dependence in aircraft. Virtually every avionics systems depends on electronics. As an extreme example, the F-16 needs three computers to control what is an inherently unstable design and turn it into one of the most highly maneuverable fighters in the world (Hallion, 1990:10). Without these computers, the F-16 cannot fly.

Because of this dependence on advanced electronic technology, a manufacturer that ceases to produce a vital component when technological advances cause it to be obsolete and unprofitable can cause an entire aircraft to become obsolete. Since the aircraft as a

whole may still excel at its mission, an accurate term for this type of obsolescence caused by DMSMS is "premature obsolescence."

Short of causing obsolescence in the entire aircraft, DMSMS causes materials shortages which impact the reparability of the aircraft components. Many components have been reduced to a single manufacturer. The problem of no manufacturers producing a component is also increasingly common. In either case, the expenses in terms of time and money are tremendous as government procurers desperately try to convince a manufacturer to produce enough of a component to keep the aircraft airborne.

The problem of obsolescence and DMSMS is not new to the Air Force. The small Air Force presence relative to the size of the economy as a whole results in a lack of incentive for continued commercial manufacturing for such a small, demanding clientele. In recent times, however, several factors have greatly exacerbated the problem of obsolescence and DMSMS as it affects the Air Force. The factors most greatly impacting these problems are the military drawdown, an extreme dependence on technology, the rapidly increasing pace of technological development, and the continued use of aircraft and systems far beyond their intended useful lives. Highlights of how each of these factors impacts obsolescence and DMSMS form the background of this thesis study.

Since the end of the Cold War, deep budgetary cuts have afflicted nearly all functions of every service. In order to streamline its organizational efficiency, the Air Force has restructured itself significantly, particularly in the area of acquiring and maintaining aircraft. The Air Force has currently reached a low in purchasing both aircraft and parts for maintenance or upgrading.

This phenomenon has great impact on Air Force systems due to an unprecedented dependence on technology. As a part of its effort to increase operating efficiency, the Air Force has developed technologies to compensate for less aircraft and less manpower. The result is an Air Force that is lighter and leaner, but more impacted by changes affecting its remaining weapons systems.

The most prominent changes come from dependence on computer technology and related integrated circuit (IC) developments. The rapid pace of turnover in integrated circuit technology was not foreseen by even the experts; looking at the trend since 1993 in Intel processors, IC technology will change significantly about every two years for the foreseeable future (Intel, 1998). Coupled with a world market which is increasingly thirsty for advanced IC technology, IC components often go out of production before completion of the lengthy process of military spending approval.

The last factor highlighted for the purpose of this study is the use of military aircraft far beyond the time period for which they were originally intended to be used. Obviously, the greatest impact of an aging fleet appears in the estimates of reliability. An AMC publication admits to having low reliability on its airlifters and cites aging systems as the cause (HQAMC/XP, 1997: 225). The majority of the US Air Force fleet is currently over 25 years old, and, as previously stated, the fleet as a whole has poor or no capability of meeting current airlift requirements (ibid.: 218).

Some aircraft in the Air Force fleet trace their origins to the 1950s. Most newer aircraft, such as the F-15E and the C-17, have designs originating in the 1980s. IC technology has turned over six times since its first appearance in 1974 (Condra, et al.,

1997:368). Since many original components are no longer produced, and commercially available replacement parts simply do not exist, obsolescence and DMSMS often lead to extensive redesign and upgrading in order both to keep airframes viable and to make it possible to have replacement parts available for the foreseeable future.

Understanding DMSMS depends on a number of divergent factors, stemming from technological, economic and political factors. Several of these factors simply do not lend themselves to modeling. Political environment and some economic factors do not offer measurable characteristics for analysis. However, many factors relating to DMSMS factors offer measurable characteristics, and these are insufficiently studied.

<u>II. Literature Review</u>

Background

The Air Force confronts many challenges today. These challenges include reduced manpower, aging aircraft, increased operations tempo, and budget cuts. All of these challenges take a toll on a vital Air Force capability, its aircraft mission readiness. In addition, another challenge has begun to impact the Air Force's ability to maintain the world's premier aerial war-fighting fleet: American industry has begun to get out of the defense industry. Every year, fewer companies produce components vital to aircraft development, production, and reparability. A term frequently applied to the problem of the shrinking industrial base is "vanishing vendors."

The problem of "vanishing vendors" comprises a twofold effect. First, sources for the manufacture of aircraft and aircraft components diminish each year. Official Department of Defense parlance dubs this effect "diminishing manufacturing sources." The second effect is the shortage in materials caused by a diminished manufacturing base, officially termed "materials shortages." Due to their intrinsic interrelationship, the Department of Defense groups these effects together, calling them Diminishing Manufacturing Sources and Materials Shortages, or DMSMS. Direction for dealing with DMSMS is found in DOD Directive 5000.1, <u>Major and Non-Major Defense Acquisition</u>

Programs, and DOD Directive 5000.2, Defense Acquisition Program Procedures (Ferguson, et al., 1990: 5).

This literature review provides a brief overview of DMSMS. The purpose of this review is to provide a description of the DMSMS situation as it relates to this thesis. The review covers the background of DMSMS with the intent of defining a framework for the context of this thesis. This review then continues with a brief discussion of the status of research for key issues in order to justify why to study DMSMS among electronics and semiconductors. The third major area of content for this literature review covers past research related to the various factors that may influence the prevalence of DMSMS among electronic components.

DMSMS Environment

DMSMS problems originate from an environment that leads to a decreased desirability or capability of production for IC's. Exactly how the environment leads to DMSMS problems is a complex issue, and no single aspect determines the extent of DMSMS for an IC or in a system. But with an overview of the environment in which DMSMS exists provides at least a suggestion of where to look for causal factors. The DMSMS environment can be divided into political and technology arenas, each described briefly hereafter.

Political Environment. In order to formulate a plan for the future resolution of DMSMS, we start with a twofold question: exactly why does the Air Force have this problem, and how did it start?

The beginnings of DMSMS are in the Department of Defense (DOD) planning process in the 1960's and 1970's. Planning for aircraft acquisition used what turned out to be two bad assumptions. These assumptions were that technology would not change significantly during the life of an airframe, and industry would always produce enough to meet DOD needs. Though these assumptions worked through the 1960's and to a lesser degree in the 1970's and 1980's, neither functions in the 1990's (Ferguson, 1990:16; Condra, et al., 1997:368).

One factor negating these assumptions includes the changed threat conditions the Air Force confronts. During the Cold War, planners easily identified the threats and Congress appropriated significant funds to combat these threats. The end of the Cold War plunged the Air Force into a world of varied missions—including humanitarian, peacekeeping and policing—against ever-changing threats (Lavoie, 1987:15; Hallion, 1990:14). Since the "evil empire" no longer is, the political environment has become increasingly difficult to convince to invest in further military technological development.

Technological Environment. In addition to the changes in the world political environment, another variable contributing to DMSMS is the pace of change in technology. Technology now advances at an ever-increasing rate unforeseen by even the experts. As an example of the rapid pace of change in technology, Condra, et al., use the Intel line of processors as representative of the rate of change of integrated circuit technology in general.

Consulting the data provided from Condra, et al., 1997 (reproduced in Figure 1), the "Interval" column displays the number of months that passed between introductions of each processor. The time decreases slowly at first until in the 1990's the time between

introductions drops dramatically to 14 months. Since the Pentium's introduction in 1993 until August 1998, Intel has introduced five improved variants on the Pentium processor, for an average turnover of just over a year between introductions of improved processors (Intel, 1998). Intel usually only continues to manufacture a processor for only a little over a year after it is superseded. Therefore, the productive life of an Intel processor currently only lasts two to three years.

Table 1. Intel Processor Development (from Condra, et al., 1997)

Processor	Speed (MHz)	Transistors	MIPS	Date Introduced	Interval (months)
8080	2	6,000	.64	4/74	--
8086	5	29,000	.33	6/78	50
80286	8	134,000	1.2	2/82	44
80386	16	275,000	6	10/85	44
486DX	25	1,200,000	20	4/89	42
486DX2	50	1,200,000	40	3/92	35
Pentium	66	3,100,000	112	5/93	14

The effect of such a short production life on DMSMS compounds the effects of political factors in the defense acquisitions arena. Congress must approve all major defense acquisitions for new aircraft or modifications to existing aircraft. The average amount of time Congress takes to approve funding for defense acquisitions is three years (Lavoie, 1987:15; Ferguson, 1990:5). Combined with an average processor production life of only three years, Congressional demands on time result in designs impossible to produce even before spending approval occurs. Even if spending approval occurred sooner, the time to

produce the first aircraft usually takes an additional two to three years later (Ferguson, 1990:11).

Couple this turnover in technology and Congressional demands on time with the fact that defense makes up a virtually non-existent percentage of the integrated circuit market, and industry has no incentive to want to produce for defense. The integrated circuit market has grown tremendously, from $26 billion in 1984 to $120 billion in 1995 (see Figure 2; Condra, et al., 1997), with high growth expected to continue for the foreseeable future. This high growth mostly results from the expanding computer market. The percent of military spending in the integrated circuit market has shrunk phenomenally from 7% in 1984 to 0.8% in 1995, or a 91.25% reduction in the integrated circuit market share in less than a decade. The extremely low volume, along with the stringently regulated and rigorous standards of the military market, simply does not provide industry any incentive to produce for defense needs, especially with the availability of the high volume, high profit commercial computer and communication markets.

Table 2. Electronics Market Volume (reproduced from Condra, et al., 1997)

Year	1984	1995	2000
Total market volume:	$26 billion	$120 billion	$300 billion
Percent of market volume:			
Computer	39%	60.3%	62.25%
Commercial	24	15.3	13.5
Communication	13	14.4	16.8
Industrial	11	6	4.5
Automotive	6	3.3	2.7
Military	7	.8	.25

To summarize the DMSMS environment, DMSMS is exacerbated by a changing political climate in which it is increasingly difficult to obtain defense funding combined with a rapidly developing technological environment. As investment in military technology slows, and IC technology develops increasingly rapidly, the military will fall further and further behind. At some point, the US technological edge in warfighting will be lost.

DMSMS Strategies

Several strategies appear in the literature for addressing DMSMS problems. Some of these strategies focus on options decision-makers and managers can use to address DMSMS. For the purposes of this thesis, these strategies will be called management strategies. In addition to management strategies, technical strategies exist which focus on component design and replacement. Synopses of the principle management and technical strategies follow.

Management Strategies. Extant literature presents numerous strategies for managing the manifestations of DMSMS. Though much expertise has focused on the technical problems of redesigning systems, a perusal of the literature also reveals important management strategies for handling DMSMS, both proactively and reactively. Though currently no strategy has been proven successful, they still merit explanation because they provide insight into the actions and functions of the major Department of Defense players in the DMSMS arena.

Four management strategies (as opposed to technical) are found in the literature. These four strategies are: 1) Plan for upgrades and modifications, 2) Manage design

changes, 3) Cooperate to form a larger market, and 4) Develop an internal production capability. A description of each follows.

Planning for Upgrades and Modifications. One way to resolve DMSMS entails setting aside funds ahead of time to accomplish periodic upgrades and modifications frequently enough that components do not have time to go out of production (Goodman, 1996:34; Lavoie, 1987:16). This option's costs in terms of funds and time to perform modifications and upgrades seem prohibitive, but the costs of acquiring an entirely new aircraft far outweigh them. For example, the acquisition costs for a B-1B totaled over $220 million per aricraft (USAF, 1999C)! A proposed upgrade to the B-1B offensive avionics computers and software as a part of the Conventional Mission Upgrade Program has an estimated cost of $179 million for 95 aircraft, or about $1.9 million per B-1B ("Boeing Wins..." 1997). Obviously, upgrading one system at a time appears far more attractive in terms of cost.

Besides possible cost savings, this option provides the benefit of the latest technology for the Air Force's premier weapon systems. Each time an airframe is modified or upgraded, replacement parts provide more up-to-date technology. This process helps maintain US Air Force military air technological superiority. Examples of successful modifications and upgrades to existing airframes are common, including the C-141 "stretch", the F-15 Strike Eagle and the C-130J.

There are two principal shortcomings to the strategy of planned upgrades and modifications. First of all, completing the upgrades to the Air Force fleet can be extremely time consuming. Another shortcoming of this solution consists of the effort to convince

Congress to approve large funds years before spending occurs. Technology experiences significant changes in the span of time it takes to achieve Congressional approval, leading to either the approval of outdated technological solutions or trying to predict accurately which modifications and upgrades run the least risk of obsolescence onto management.

Managing Design Changes. Managing changes so that only components with relatively long production lives comprise design plans can greatly extend the life of aircraft (Condra, et al., 1997:370; Lavoie, 1987:15). Components have different production lives depending on their content of "cutting edge" technology and their sustainable marketability. When a specific component has wide-spread applications, or becomes a standard, production longevity will likely increase correspondingly. On the other hand, components with a limited range of use will likely have a short production life.

This option requires more funds up front to purchase the most advanced technology, but such components generally take longer to fall into obsolescence. Unfortunately, the most advanced technology has the least likelihood of being adopted due to its cost and the time requirements imposed by the acquisition process. Furthermore, since even the most advanced technology soon becomes outdated, this option forms only part of a solution to DMSMS. Managing design changes works best when used in conjunction with upgrades and modifications. By managing design changes so that design components that do not suffer DMSMS as quickly are selected, the time necessary between performing an upgrade or modification can be extended. Longer intervals between upgrades and modifications translate into less frequent changes to the airframe as well as less requests for funding.

Cooperate to Form a Larger Market. If the military constituted part of a larger market segment, the greater profit expectation resulting from the larger market would entice industry to continue producing for the market, and thus provide for defense needs (Condra, et al., 1997:369). For this solution to function, another significant industry with needs similar to the military's must exist. The military would have to share standards and demand similar components in order to form a large enough market to effectively entice industry into continued production of obsolete components.

Unfortunately, few industries share military needs or require such stringent testing. The outdoor electronics market uses many military standards, but currently forms an even smaller share of the integrated circuit market than the military. However, Air Force policy has slowly changed, and continues to change, allowing the use of more universal commercial and performance based standards. The migration towards commercial standards officially began with a 1994 memorandum from Defense Secretary William Perry (Perry, 1994). The C-17 currently has a blanket exemption from using MILSTD. This topic appears later in the literature review.

Develop an Internal Production Capability. The military does possess a limited organic production capability. "Organic" refers to an internal capability or capacity. In the absence of commercial production competition, the military could cultivate its organic production capability so that it provides for defense requirements (Condra, et al., 1997: 369). Up to now, no literature addresses the costs entailed by such an enterprise, so a realistic cost comparison with the current system of procuring a company to produce a small

batch of an out-of-production component needs to be accomplished to establish this option's relative efficiency.

Generalized Emulation of Microcircuits Enterprise System (GEMES) and Defense Microelectronics Activity (DMEA) are two DoD related programs which seek to develop a limited capacity to continue organic production of much needed but obsolete electronic components. GEMES is a program designed to provide continued production capability of microcircuits using Generalized Emulation of Microcircuits (GEM) technology. This is done via a contract with a civilian corporation, Sarnoff Corporation, that provides manufacturing facilities (GEMES, 1999).

DMEA is the DoD's designated executive agent for IC microelectronics DMSMS, handling DMSMS among IC's as a horizontal, technology based issue. DMEA is involved in virtually all aspects of DMSMS management for IC's at the DoD level, seeking to coordinate efforts both internally and externally to achieve greater economies of scale and information sharing (DMEA, 1999).

Technical Strategies. Integral to the management of DMSMS strategies are the solutions that must be chosen based on the analysis of technical and cost considerations. Current literature exhibits numerous studies of technical (as opposed to management) resolution strategies for DMSMS issues. These solutions all involve engineers and subcontractors to decide which procurement strategy alleviates the DMSMS problem.

A succinct and comprehensive description of fifteen options for resolving DMSMS problems appears in the *Case Resolution Guide* published by the Air Force Materiel Command DMSMS program (DMSMS program, 1998). These fifteen DMSMS resolution

options can be condensed into eight primary actions. This is possible due to the similarities in actions required by some of the options. These eight actions are: life of time (LOT) buy, substitution, reverse engineering, redesign, reclamation, emulation, aftermarket manufacturers, and develop a new source. These options are described in the following paragraphs:

Life of Time (LOT) Buy. Previously a common strategy for resolving DMSMS, LOT buys purchase a sufficient quantity of a DMSMS item to meet total demands of affected systems for their expected useful life. This option often requires large one-time buys, for which supporting funds may be difficult to obtain. This option may also become undesirable when a redesign could yield benefits of additional part effectiveness at a justifiable cost (DMSMS Program, 1998: 55-57).

Substitution. This option means replacing a DMSMS item with a usable part that does not fall outside of certain conformance specifications. Commercial off the shelf (COTS) programs are an example of substitution. The problem lies in the degree of nonconformance of the substitute's specifications to the original part's specifications (DMSMS Program, 1998: 48-49).

Reverse Engineering. When original DMSMS item technical plans are not available, it may become necessary to reverse engineer: take the item apart or otherwise analyze its design. Generally the purpose is to build exact replicas of the original part. Reverse engineering usually incurs heavy expenses (DMSMS Program, 1998: 68-69).

Redesign. This option becomes desirable when system improvements become necessary. Redesigning items, like emulation, involves a certain risk of undesired

functional responses under certain circumstances (DMSMS Program, 1998: 63-64). An attractive possibility during the redesign process is upgrading the component, but this can quickly becomes complex as the part must still interact with other, already existing parts and systems and also entails a certain risk of undesired functional responses under certain circumstances (DMSMS Program, 1998: 65).

Reclamation. Reclamation is basically salvage. Sources for salvage include beyond economical repair equipment at government repair facilities, surplus (either government or commercial), and items garnered from decommissioned or deactiviated units. This solution should only occur in answer to a crisis or some unavoidable circumstance. Reclamation as a resolution option provides short-term relief at best (DMSMS Program, 1998: 60-62).

Emulation. The program goal of the Generalized Emulation of Microcircuits Enterprise System (GEMES), the official DoD source of integrated circuit emulation, "...is to rapidly and economically provide exact replacements for obsolete IC devices." (GEMES, 1999). Extending this idea outside of GEMES and to components other than IC devices embodies the meaning of emulation in the general DMSMS related sense. Though emulation has enjoyed several successes in the DoD, a risk exists that the alternative, emulating part may not function exactly the same as the original under all circumstances. This option can also entail heavy up-front engineering expenditures, though for parts with widespread applicability, these up-front costs diminish as they average over more units of production (DMSMS Program, 1998: 52-54).

Aftermarket manufacturers. Occasionally, certain manufacturers can be convinced to assume production of certain DMSMS items. This requires a transfer agreement from the original equipment manufacturer (OEM). However, care must be taken by the procurer to ensure the aftermarket manufacturer builds to original equipment specifications (DMSMS Program, 1998: 45-47). Another option to take advantage of existing aftermarket manufacturers would be to convert the part specifications from military specifications to performance based specifications, following civilian commercial market practices (DMSMS Program, 1998: 41-43). Alternately, requirements can be redefined to accept commercial off-the-shelf products (DMSMS Program, 1998: 50-51).

Develop New Source. If the DoD can access complete manufacturing technical data for an item, it can contract to recommence production of that item. However, emulation or redesign could provide cost-comparable options that could provide the additional benefits of improved performance, reliability, and maintainability (DMSMS Program, 1998: 58-59).

To summarize DMSMS strategies, research journals and the Air Force DMSMS Program Office both present strategies for either preventing or diminishing DMSMS. These strategies depend either on managerial or technological prowess, or a combination of both. Though some of the solutions offer some prevention capability, most revolve around how to deal with an already present DMSMS problem.

Key Issues: Why Study Electronics/Semiconductors?

An aircraft consists of numerous components: mechanical, electrical, structural and electronic. Why focus on electronics components for the purpose of studying DMSMS? Many considerations point to electronics as a vital area of DMSMS concern. This section highlights the most important characteristics of electronic and semiconductor components that make them amenable to thesis study.

Identified as a Problem Area. The first page of the DMSMS Case Resolution Guide (DMSMS Program, 1998) says: "The majority of DMSMS problems occur in the area of electronic components (primarily microcircuits)..."

Most other literature also closely identifies the problem of obsolescence and DMSMS with the electronics industry. Condra, et al., (1997) discuss the vanished assumption of component permanence in aerospace electronic equipment. More specifically, their article focuses on the problem of electronics components obsolescence afflicting the military.

Lavoie and Culp (1987) discuss obsolescence in terms of the acquisitions process. They also highlight electronics as a major factor in the obsolescence problem, particularly in a development process that takes 15 years to develop a new aircraft (p. 16).

Acknowledgment of the importance of electronics to DMSMS appears in Defense Secretary William Perry's 1994 memorandum addressing the reform of MILSTD and MILSPEC standards. The memorandum is an attempt to facilitate replacement of DMSMS afflicted components via COTS technology and the use of performance-oriented standards in order to ease the acquisition process for replacement of DMSMS components.

Data Availability. DMSMS encompasses many areas of concern, including political and economic factors as well as technical characteristics. The difficulty in attempting to measure levels of DMSMS, then, lies in finding those characteristics that are measurable. Not only must they be measurable, they also must have a source that makes them readily available to be measured. Several up-to-date sources of electronic component characteristics exist, the majority of which may be accessed via the Internet.

Information Handling Services, Inc. (IHS) maintains the largest and most complete database of electronic components and their characteristics. Accessible over the Internet, this database provides detailed electronics parts information organized into several different databases. Recently, IHS joined forces with the leading DMSMS prediction tool developer, Manufacturing Technologies, Incorporated (MTI). In this relationship, IHS provides the part technical characteristic data, while MTI tracks how many manufacturers exist for a given part as well as providing a prediction as to future availability of a queried part.

One of the IHS databases, CAPSXpert, and an MTI database, PARTSXpert, comprise the majority of the data used in this thesis study. Electronics components information included in CAPSXpert include operating temperatures, package configuration, number of pins, type of component, process technology used to manufacture the component, voltage, manufacturers, and part numbers. Users can access specific components via part number. Users may also look up all of a particular type of component. From inside the CAPSXpert database, the PARTSXpert database can be accessed in order to view MTI's assessment of the number of remaining manufacturers for a part as well as predicting its availability into the future. These databases were chosen because they form the basis of Air

Materiel Command's DMSMS Program Office's database of choice, AVCOM (published by MTI).

AVCOM provides some of the information from CAPSXpert and PARTSXpert, but the data is aligned schematically as they would be found in specific aircraft, showing the aircraft level, then progressively going into the line replaceable units (LRU's), shop replaceable units (SRU's), and on down to the individual part for the aircraft being researched. At each level an assessment can be requested showing a breakout of how many components which comprise the part being analyzed are on the verge of going out of production, how many are not in production, and whether a LOT buy has been accomplished. AVCOM is updated quarterly for use by Air Force Special Program Offices and the DMSMS Program Office.

Questlink (http://www.questlink.com) is an online site with free access to several engineering information sources, including databases on transistors, IC's, and other electronic components. Questlink provides a single site from which to access original manufacturer product datasheets as well as other performance and price-related data.

Electronics Obsolescence is Already Well-Studied. The study of obsolescence as it affects electronic components comprises much of the extant DMSMS literature. Two early studies of the current trend of obsolescence of IC's and semiconductors appeared as Air Force Institute of Technology Master's theses in the early 1980's. More current research efforts exist in both the defense and commercial research venues. A brief discussion of the two early 1980's theses, a current thesis, and a commercially funded study follow.

In his 1981 Master's degree thesis (Brooks, 1981), Capt. Michael E. Brooks published a study into the use of time series growth curves as predictors of DMSMS for electronic components. Using commercial sales data, Capt. Brooks successfully used S-shaped curves to describe growth patterns of three classes of electronic components. His methodology incorporated the use of a technological forecasting technique called trend extrapolation. Using obsolete electronic components representing three families of technologies with sales data as the dependent variable and time as the independent variable, he concluded that there exists a predictable pattern of economic growth based on component technology. Capt. Brooks also concluded that when a product entered the declining stages of its life-cycle, the forecasting of DMS becomes feasible. His findings found that DMS occurred at or near the saturation level of the growth curve for each technology. However, due to the small sample size of only three technologies, no conclusion could be drawn as to the relationship between families of technologies and DMSMS.

In their 1982 Master's thesis, Fisher and Sheehan also analyzed economic factors related to DMS afflicted items. They cite electronics as the principle culprits (Fisher and Sheehan, 1982: 32-33). Their study focused on life-of-type buys, using economic rather than technical data. In their study, future demands and costs served as independent variables for determining an economical LOT buy quantity. The result was a simple linear regression model and sensitivity analysis. However, they assumed constant demand using demand levels for the two years prior to the LOT buy, which may or may not provide an accurate forecast of demand. Their results indicated that while demand remains stable for most items, those with static demand require differing buying methods to properly manage DMS.

Another significant finding of their study concerned which demand patterns seemed common to DMS afflicted components: mainly those items with medium or low demand categories which are stable over time (*ibid.*: 91).

DMSMS studies in the mid-1980's to early 1990's become scarce, perhaps due to increased military spending. However, the problem of DMSMS did not abate. The two industry leaders in commercially available DMSMS management services, MTI, Inc. and TACTech, were both formed in the 1980's. Despite their (at times) different methods, both companies have concentrated almost exclusively on electronic components as the primary propagators of DMSMS.

Renewed academic interest appeared in a 1998 thesis study by Capt. John Bell, who studied the prediction and response to DMSMS in the F-15 radar system (Bell, 1998). Capt. Bell chose the radar system as the subject of his investigation because of its relatively well-documented history of DMSMS and because an "[i]n-depth analysis of the F-15 radar's databases provides a clear picture of the impact obsolescence and DMSMS can have on an aircraft's electronic systems." (Bell, 1998: 30). Bell focused on parts unique to a single radar system, finding that unique parts suffer far more DMSMS than parts common to several systems. Also, a single part suffering DMSMS problems may occur multiple times throughout an electronics system, thereby turning a shortage of a single component into a widespread problem. DMSMS managers need to be aware of where each part lies in the overall system, and DMSMS must be tracked continuously at the level of individual components. Bell found that the newer radar systems did not suffer less, and may suffer more, DMSMS than older radar systems. This implies that other factors, such as rate of

development for different technologies or economic factors influence the appearance of DMSMS. Most importantly, by looking at a radar system that had almost been discontinued due to a significant DMSMS problem, Bell found that proper logistical management of DMSMS and obsolescence could indeed convert an aging system into a viable system. Logistics information systems were singled out as the vital tool in DMSMS management in electronics obsolescence.

Offers Most Potential Benefit. If electronics obsolescence forms the greater part of the DMSMS problem, then controlling or managing electronics obsolescence also offers the most potential benefit for reducing long-term effects of DMSMS. Previous studies indicate that monitoring and predicting DMSMS can potentially yield benefits in DMSMS management. Electronics represent a major problem area, which have been extensively studied. Furthermore, substantial, though disparate, sources of data exist that track electronic part characteristics and DMSMS status. Maximizing potential research benefit depends on both data availability and the possibility that DMSMS can indeed be controlled by proper management tools and techniques.

Methodology Issues

In studying DMSMS, a multitude of factors could be relevant. Therefore, the vital question to create a DMSMS model becomes "Which factors do we study?" Fortunately, past studies have established certain credible, measurable item characteristics. These factors derive from both technically related item characteristics, such as item technology family, voltage, or design age, and economic factors, such as demand volume or whether it's a

military specific design or has widespread commercial application. This section discusses both the technical and the economic item characteristics chosen to measure DMSMS related factors for this study's model.

Technical Factors. The six factors chosen for this thesis study were chosen because of their presence in DMSMS-related and electronics industry literature. A brief synopsis of some of the literature describing each follows.

Age of Design. Much literature exists regarding the rapid pace of development in electronics technology. The earliest documented observation on the pace of technological turnover among semiconductor memory chip performance is Moore's Law. While preparing for a speech in 1965, Gordon Moore realized that chip technology doubled about every 18-24 months (Intel, 1999a). This observation remains fairly accurate to this day, and functions well when applied to related technology such as microprocessors, as demonstrated by Intel's accurate application of Moore's Law to its own line of processors from 1971 through their projected release of the Micro 2000 (*ibid.*).

Research specific to military application of electronic components also relate obsolescence to aging designs and technologies. Drawing on several sources, Condra, et al., related rapidly technological turnover in commercial industry to increasing problems with obsolescence for the military (Condra, et al., 1997).

Another study indicted development times in avionics acquisition as a leading cause of component obsolescence among Air Force aircraft systems (Ferguson, 1990: 11; Lavoie, 1987: 16). Because of long development times caused by political and bureaucratic forces, "...you find that components go through two major economic lifetimes before you can get

the first rubber on the ramp." (Lavoie, 1987: 16). In other words, many electronic components become obsolete before an aircraft or a major upgrade to an existing aircraft even has time to receive approval.

Semiconductor Type. Most modern electronics consist of semiconductor technology. Some of these types of semiconductors experience different rates of innovation, either due to their amenability to innovation or because of their stage of development in the product life-cycle. There are three main classes of semiconductors based on their construction.

One type of semiconductor, integrated circuits, which includes microprocessors, is particularly amenable to innovation. An integrated circuit is:

"An electronic circuit in which many active or passive elements are fabricated and connected together on a continuous substrate, as opposed to discrete devices, such as transistors, resistors, capacitors and diodes." (Harris Semiconductor, 1999).

Another type of semiconductor is the discrete semiconductor. Discrete semiconductors are defined as:

"A class of electronic components, such as power MOSFETs, bipolar power transistors, surgectors, MOVs, optoelectronic devices, rectifiers, power hybrid circuits, intelligent power discretes, and transistors. Typically, these devices contain one active element, such as a transistor or diode. However, hybrids, optoelectronic devices, and intelligent discretes may contain more than one active element. In contrast, integrated circuits (ICs) typically contain hundreds, thousands, or even millions of active elements in a single die." (Harris Semiconductors, 1999).

The third type of semiconductor is the hybrid semiconductor, defined as:

"**(1)** A combination of passive and active subminiature devices on an insulating substrate to perform a complete circuit function. **(2)** A combination of one or more integrated circuits with one or more discrete components. **(3)** The combination of more than one type of integrated circuit into a single package." (Harris Semiconductor, 1999).

The effect of semiconductor type on DMSMS has yet to be analyzed. However, some research indicates that part classification may affect obsolescence and production (Brooks, 1981; Condra, 1997; Cooper, 1999). Parts with minimal performance improvement potential, such as transistors, simply do not suffer obsolescence. Despite the limited research, no conclusive evidence exists that analysis at the level of semiconductor type does have a quantifiable relationship with DMSMS. Additional research is needed to establish whether there is indeed a tie between semiconductor type and appearance of DMSMS.

Function. Semiconductor electronics are designed to fulfill certain useful functions. Some semiconductors fulfill the role of storing information, such as memory. Other semiconductor functions include logic circuits, microprocessors, and transistors. For reasons of parsimony, components tend to be as simple as possible while still fulfilling a needed function. Electronic components with very simple or straightforward functions, such as transistors or memory, may exist for years with little change, whereas the complex integrated circuits which may fulfill multiple functions, such as microprocessors, experience design changes fairly frequently (Condra, et al., 1997: 368; Cooper, 1999; Martin, 1999).

Because different functions may experience design changes more or less often, these design changes may lead to DMSMS problems as older designs are often superseded by new designs. More research needs conducted to analyze the relationship between function and DMSMS presence to discover if there are indeed differing rates of technological turnover and obsolescence for each functional area of semiconductors.

Process Technology. The advances in integrated circuit technology usually follow advances in manufacturing process technologies. Different manufacturing process technologies have different limitations for fitting more circuitry into a smaller chip size, or reducing voltages, or both (Cooper, 1999). The electronics industry, like any other industry, tends to adopt newer process technology as it becomes available and affordable in order to keep quality high and costs low.

Most research into process technology discusses changing trends in uses of the different processes. Like many areas of technology, newer improved process technologies tend to supersede previous processes. DMSMS presence may well depend on the process used to manufacture the technology.

Die Size. A die is "A single square or rectangular piece of semiconductor material into which a specific electrical circuit has been fabricated. Plural: dice. Also called a chip." (Harris Semiconductors, 1999). One of the principle advances in IC technology has been reduction in size. Reduction in die size is the impetus behind Moore's Law (Intel, 1999a), enabling ever-increasing IC capability by fitting more circuitry per square millimeter. Trade news sources report that 0.13 micron (millionths of a meter) are planned for release in the year 2002 (Robertson, 1999). In comparison with 1997 technology, Intel's Pentium II processor's die size is 0.35 microns (Intel, 1999b).

Manufacturers continually seek smaller die sizes in an effort to create better IC's in order to gain an advantage over competing manufacturers in the market. As one manufacturer releases a smaller die size, competitors must seek to match or beat the decreased die size in order to offer the consumer a better product. It seems reasonable that

as die sizes decrease, the older IC's that do not have the die size advantage will more quickly go out of production. Currently, no research exists that analyzes the relationship between the trend in decreasing die size and DMSMS.

Voltage. Along with decreased IC die size, voltages are on the decline. Decreased voltage results in not only less energy consumption, but decreased heat generation, which in turns results in greater reliability (Gibbs, 1999). Lower voltages also mean more portability and improved performance. Texas Instruments plans to finally go below the 1 volt power requirement level for a new IC planned for introduction in the year 2000 (Lineback, 1999). Pentium II processors operate at 3.3 volts with a different core power requirement of 2.8 volts, whereas the original PC ran at 5 volts (Intel, 1999b).

As with die size, lower voltage IC's have a technological advantage that improves their desirability for end-use. It remains to be seen whether as lower voltage IC's appear that they will supplant higher voltage IC's. But it seems reasonable that improvements to IC design may lead to decreased production of older, "unimproved" designs.

Economic Factors. Companies do not decide to stop producing for defense needs simply because a new technology or more advanced circuitry becomes available. Companies have a profit motive, and will produce as long as profit potential exists. A small number of factors primarily determine the profitability of continued production of particular product. A synopsis of literature relating these economic factors to DMSMS follows.

Demand. Demand appears strongly correlated with the advent of obsolescence and DMSMS, as it determines volume of production (Brooks, 1981; Condra, et al., 1997; Fisher and Walter, 1982; Lavoie, 1987; Martin, 1999). The military market no

longer forms a significant portion of the electronics market, currently comprising less than 1% of the total electronics and IC market (Condra, et al., 1997). This means industry goes elsewhere to earn the overwhelming majority of its profits, leading to the erosion of military influence on industry (Condra, 1997: 368; Lavoie, 1987: 16; Martin, 1999). Two common ways of measuring volume exist: number of units sold, and dollars of sales. Some past research indicates both units and dollars provide equally valid measures of volume as it relates to DMSMS (Brooks, 1981: 68). Also, whether the volume is in the process of increasing or decreasing determines whether the component is growing or declining.

Military Market. Military electronics were once considered immune to obsolescence; at one time, unlimited budgets and strong military support in Congress facilitated the military acquisition process greatly (Ferguson, 1990: 11; Lavoie, 1987: 16). However, the explosive growth of high volume electronics industries such as computers and telecommunications has made low volume, complex systems (such as those used by both the commercial and military avionics industries) financially less beneficial (Condra, et al., 1997: 368). The rapidly diminishing defense industrial base led Secretary of Defense William Perry to publish a memorandum directing a move away from military specific standards to a more commercially accepted performance standard for component acquisitions (Perry, 1994).

Though the decreasing military market may seem like a volume or demand related issue, it differs in that the undesirability for production of military parts stems from characteristics specific to the military market. To begin with, military procurers require compliance with strict standards of reliability and ruggedness. This causes increased costs

for the manufacturer who must develop and test their IC's. Also, military specifications are often very detailed, making development less flexible. The commercial market generally demands IC's based on their performance versus the military policy of compliance with standards. It is simply easier and cheaper to produce one IC that satisfies a variety of commercial needs, versus the military policy of producing many different IC's specific for only one or two uses.

The dwindling of the defense industrial base means that military specific parts suffer increasing risk of going out of production. Secretary Perry's memorandum opened the doors for commercial-off-the-shelf replacement of components, the underlying idea being that joining the larger commercial customer base provides an increased profit incentive for manufacturers to continue producing to meet demand (Condra, 1997: 369; Perry, 1994).

III. Methodology

Chapter I set forth the basic research questions of this thesis. The questions address two primary areas of concern. The first area of concern is whether the data indicate the existence of a clear relationship between IC characteristics and DMSMS occurrence, and how much each IC characteristic affects DMSMS rates. The second area of concern is whether the existing databases provide sufficient information for future use in predicting DMSMS occurrence among IC components. This chapter details the procedures for answering the basic research questions as laid out in chapter I.

Experimental Design

While a valid model by itself will not answer all the research questions presented in Chapter I, it would provide a strong basis upon which to build the conclusions. In turn, answering each of the questions proposed in Chapter I will fulfill the objectives of this thesis effort. Each question will be addressed in Chapter IV, Analysis of Results, and Chapter V, Conclusions.

In order to confirm that each question is answered, a hypothesis relevant to each question follows. Answering each hypothesis in turn answers its respective question. A list of the questions from Chapter I and their respective hypotheses ensues in the following

paragraphs. Sometimes more than one question will be answered by finding the answer to one hypothesis.

- Is there a pattern to the characteristics of DMS afflicted versus non-afflicted parts?
- What characteristics form this pattern?
- How much does each of these characteristics affect obsolescence?

  H_0: A regression model can not be used to relate DMSMS presence to parts characteristic(s).

  H_a: A regression model can be used to relate DMSMS presence to parts characteristic(s).

- Can we use this discernible pattern (if there is one) to make predictions about the degree of DMS afflicting a part?

  H_0: The regression model cannot make predictions regarding DMSMS presence for a part.

  H_a: The regression model can make predictions regarding DMSMS presence for a part.

- How applicable is this research in the event a new technology becomes available?

  H_0: The regression model cannot be used in the event of the introduction of a new technology.

  H_a: The regression model can be used in the event of the introduction of a new technology.

- Do current databases provide sufficient information to make predictions on DMS prevalence?

  H_0: Existing databases do provide sufficient information to make predictions about DMSMS presence.

  H_a: Existing databases do not provide sufficient information to make predictions about DMSMS presence.

In order to address these research questions and relevant hypotheses, an experiment must be conducted. The design of this experiment must address the choice of the response variable, the selection of the independent variables, and how the independent variables are measured. Concomitant to the design of experiments is the sampling method chosen and

selection of the mathematical model used to describe the experiment, both of which are discussed in separate sections after the design of experiments.

Response Variable. The response variable used to measure DMSMS was selected based on the convention for tracking DMSMS presence that is most prevalent in the DMSMS literature. This convention is the "stoplight" scale used by DMSMS industry leader, Manufacturing Technology, Inc. (MTI). The colors of the "stoplight," also called flags, represent how many manufacturers exist for a given integrated circuit (IC). A red flag means no manufacturers, yellow means only one manufacturer, and green means more than one manufacturer exists for a given IC.

MTI's PARTSXpert database (described later in this chapter) provides two flags, one for generic part availability, the other for the availability of the specific combination of IC physical packaging and generic part. After a consideration of the characteristics of each flag, it was decided to use the generic flag instead of the generic/package combination flag. This is because this thesis seeks differences in the IC design and technology themselves ending in obsolescence rather than whether a certain configuration of housing material and pins for a particular IC design goes out of production. Additionally, different package configurations are often interchangeable or at least easily adaptable, being the difference between a plastic and a ceramic housing, for example. Therefore, a red flag on a certain package and generic IC part number in reality may not indicate an obsolescence problem if another package and generic IC part provide a suitable substitute. A red flag on the generic IC part, however, means there is no hope of finding another compatible IC or negotiating with the manufacturer to provide the IC with a different package configuration. Based on

these considerations, the decision was made to use the generic flag as the basis for the response variable in this thesis.

Independent Variables. Independent variables were chosen based on their possible relevance to obsolescence as discussed in the literature review, as well as the availability of data. Though there are many independent variables that could possibly affect DMSMS, five were chosen. Each is briefly described below along with the possible levels for each of these factors.

Functional Class. There are fifteen functional classes of IC's. These are analog, ASIC/programmables, consumer, converters, digital signal processors (DSP), industrial control, interface, logic, memory, microcontroller, microprocessor, oscillator, peripheral, sensor, and telecomm/datacomm. These functional classes form a mutually exclusive and exhaustive taxonomy of all parts in the study.

Technology. This is the technological basis of the part's manufacturing process. Most IC's used CMOS technology, but other technologies included in the data for this thesis are BICMOS, TTL, bipolar, GAAS, MOS, ECL, and hybrid. Other technologies present in the database but not included in the study are BCDMOS, CCD, MNOS, and SNOS. Hybrids include all items that rely on more than one technology. Additionally, commonly combined technologies are both listed rather than falling under the hybrid category, so these categories are not mutually exclusive.

Voltage. Treated as a continuous variable and a nominal variable since voltages are reducing by increments, such as from 5V to 3.3 V.

Military Specificity. A binary variable, simply a zero for a non-military specific part and a 1 for parts designed for military use. Parts used by the military but not designed specifically for military use would be a "zero". A good example is the Pentium processor, many of which are used in government desktop computers, but the Pentium is not designed specifically to meet military standards of ruggedness.

Design Age. A continuous numeric variable, design age is the time, in years, since the IC became available for purchase. The reference date for measuring age is from 10 July 1999.

These independent variables were selected both because of their possible relation to DMSMS and their availability in the databases. Each will be regressed individually as a single factor against the dependent variable. Then the factors with the strongest observed significance levels and demonstrated usefulness will be combined into a multiple regression model.

Data Sources and Descriptions

Two main sources of data for IC's were used for this thesis. The primary data source consists of the suite of databases maintained by Information Handling Services, Incorporated (IHS). This suite of multiple databases provides electronic component characteristic data in the CAPSXpert Semiconductors database, and availability (i.e., DMSMS status) coding in the PARTSXpert database. The second main source of data for IC's appears in the product datasheets, which provide dates for the age of the components' design. A description of each data source follows.

The Databases. Two primary databases form the source of the thesis data, CAPSXpert and PARTSXpert. IHS created and maintains the CAPSXpert database, which provided the technical and engineering data, such as voltage, manufacturing technology, and design age. Manufacturing Technology Incorporated's (MTI) PARTSXpert database provides a summary of the DMSMS status, the flag for number of manufacturers of the generic component.

Each of these companies further uses these databases to produce customized services to various customers, such as the Avionics Component Obsolescence Management (AVCOM) software which provides the Air Force with a DMSMS management tool specific to Air Force weapon systems. For this thesis, the two main databases, CAPSXpert and PARTSXpert, provided access to all the electronic components technical data required.

The CAPSXpert Semiconductors database consists of technical data on over 2.7 million semiconductors, including 772,505 IC's, 127,465 optoelectronic semiconductors, and over a million discrete semiconductors. CAPSXpert provides the technical specifications data, including part number, manufacturer, supply voltage, manufacturing process technology, and whether the component meets the guidelines for military use requiring high reliability. CAPSXpert also provides access to manufacturer product datasheets.

Data can be called up by part number, keyword search, or manufacturer name. An additional method of parts look-up is the "Parametric Search," which organizes all parts by functional category, such as digital signal processor, memory, or microprocessor. Component data used in this thesis was looked up with the "Parametric Search" function of

CAPSXpert. The exact technique used to select components and look them up in the database is discussed under sampling techniques.

Once an individual component is called up in CAPSXpert, a link to PARTSXpert becomes available. PARTSXpert is an online service that provides data specific to DMSMS management at a component level. PARTSXpert provides two services for DMSMS managers. One is a prediction of future availability for an individual component, based on current DMSMS status, industry trends and technology. The second PARTSXpert service is an evaluation of the current number of manufacturers for individual components, which is considered valid for the next year. This evaluation uses a "stoplight" color scale of red, yellow, and green. Red indicates the component is out of production. Yellow means only one manufacturer exists or none exists but current needs are met by on-hand stock or a pending life-of-type (LOT) buy. Green means two or more manufacturers exist, with no known plans to terminate production.

PARTSXpert actually provides two evaluations. One is for the generic part, which is the most basic configuration of the component. To understand the concept of a generic part, we can draw on a widely known example, the RAM in a desktop personal computer (PC). When someone talks about a 16-MB upgrade of EDO RAM for his PC, he is speaking in terms of a generic part. The second availability flag is for the generic part and package combination. The package is the physical form of the component. In other words, to continue with the example of the PC, the user requires not just any 16-MB EDO RAM, but it must also meet the package requirements of being in the configuration of a SIMM (single

in-line memory module) with a 72 pin connection, which is the industry standard for desktop EDO RAM packaging.

For this thesis, only the flag for the generic part availability is used in the belief that the only general technological turnover is truly important to DMSMS occurrence. The package requirements may vary by industry and do not tend to change over time for a given generic part.

Product Datasheets. Product datasheets provide information to the buyers and users of their respective components. Since no standard product datasheet format exists, each manufacturer decides on its own what information to provide, though every datasheet as a minimum is supposed to provide information necessary to enable use of the product by the purchaser. For the purposes of this thesis, the only data taken directly from the datasheet is the date of publication for the datasheet. This information serves to date the design of the component. In many instances a half dozen or more updated datasheets existed for a single IC, with no change to the part number. Where multiple datasheets exist for a single IC, the datasheet with the oldest date was used in order to find the date closest to the original design date.

Though actual product design precedes the datasheet date, the datasheet dates coincide closely with the release of the product on the market, which is the earliest point in time at which a user could make use of the design.

Sample Descriptions, Limitations, and Generalizations

Since the CAPSXpert Semiconductors database consists of more than 2.7 million components, an analysis of the entire population was infeasible. Therefore, random sampling was used to obtain a representative sample upon which to build a statistically significant model.

CAPSXpert contains data on integrated circuits, discrete semiconductors, and optoelectronics (which generally include many hybrid components). For the purposes of this thesis only the integrated circuits were used. Design age was considered a vital piece of information, and all referenced integrated circuits had datasheets with design dates. Unfortunately, the CAPSXpert database did not provide any design date information or product datasheet links for discrete semiconductors, perhaps owing to their simplistic end-user implementation.

The sample was derived using proportional stratified sampling with strata based on IC functional class. This was done for two reasons. First, it was believed that stratification by functional class might increase statistical precision by allowing identification of different DMSMS rates by functional class. Stratifying by function allows analysis of IC's by function to provide clearer insight into the DMSMS phenomena. Also, stratifying by function facilitated the sampling process, allowing the writer to take advantage of the "Parametric Search" function of CAPSXpert, which organizes the database by function.

Descriptive statistics of the population were found by using a counting ability in the CAPSXpert database that allows counts of certain IC characteristics to be performed. Counts were done by function, voltage, technology, and military specificity. Since design

age required reference to a separate database of datasheets, it was not practical to acquire descriptive statistics of the design ages for the entire database since it would require perusal of 777,278 datasheets--an endeavor far outside the scope of this thesis effort. Table 3 summarizes the descriptive statistics of the sample versus the population for function, voltage, technology, and military specificity, respectively.

For the sample, functional classes that comprised less than 1% of the total database population were excluded from the sample for analysis. The three excluded functions were digital signal processors, oscillators, and sensors. A proportional representation of these functions would have required a sample size far in excess of the limitations of this thesis since these functional classes each comprise a mere 0.2% of the population. The final list of functional classes included the following classes of integrated circuits: analog, ASIC/programmables, consumer, converter, industrial control, logic, memory, microcontroller, microprocessor, peripheral, and telecomm/datacomm.

To select individual components to sample, CAPSXpert has no command to pull up a list of specific manufacturer part numbers. However, it does have the ability to provide a list of alphanumeric generic part numbers (generic parts are defined earlier in this chapter). Once the total number of generic part numbers was known for each functional class, the random number generator in Microsoft Excel's Data Analysis Pak was used to randomly select the generic part numbers for each functional class. This was done by creating a uniform random distribution of numbers from 1 to the n for each functional class, then annotating the nth generic part number from the complete list of generic part numbers for that functional class.

Table 3: Comparison of Population and Sample Representations

Whole Population of database of IC's=777,278

Function	% of Database	% of Sample	Technology	% of Database	% of Sample
Analog	11.0%	11.1%	All CMOS	60.2%	57.0%
ASIC/Programmables	5.8%	6.0%	All BICMOS	2.2%	8.1%
Consumer	0.9%	1.3%	TTL	16.9%	14.0%
Converter	3.6%	3.8%	Bipolar	11.8%	8.1%
DSP	0.2%	N/A	ECL	1.3%	0.9%
Industrial Control	0.9%	1.3%	MOS	4.0%	2.6%
Interface	5.1%	4.7%	BCDMOS	0.1%	0.0%
Logic	27.7%	27.2%	CCD	0.0%	0.0%
Memory	34.4%	34.0%	GAAS	0.3%	2.1%
Microcontroller	3.7%	3.8%	MNOS	0.0%	0.0%
Microprocessor	1.2%	1.3%	Hybrid	2.7%	6.8%
Oscillator	0.2%	N/A	SNOS	0.0%	0.0%
Peripheral	3.1%	3.4%	BTL	0.0%	0.0%
Sensor	0.2%	N/A	DTL	0.3%	0.4%
Telecomm/Datacomm	2.0%	2.1%	HNIL	0.1%	0.0%
Total n	**777,278**	**235**	I2L	0.0%	0.0%
% of database	**100.0%**	**0.0302%**	JFET	0.0%	0.0%
			Total n	**769,551**	**235**
			% of database	**99.0%**	**0.0302%**
Voltage			**Military**		
<1	0.2%	0.0%	Yes	23.1%	21.3%
1	1.0%	2.1%	No	76.9%	78.7%
2	4.0%	3.0%	**Total n**	**713,013**	**235**
3	12.7%	15.4%	**% of database**	**91.7%**	**0.0302%**
4	1.0%	0.4%			
5	75.1%	70.1%			
6	0.3%	0.0%			
7	0.0%	0.4%			
8	0.1%	0.4%			
9	0.2%	0.0%			
10	0.1%	0.0%			
11	0.0%	0.4%			
12	0.8%	1.7%			
13	0.0%	1.3%			
14	0.0%	0.9%			
15	3.9%	0.9%			
16+	0.4%	3.0%			
Total n	**675,166**	**234**			
% of database	**86.9%**	**0.0301%**			

To select individual components to sample, CAPSXpert has no command to pull up a list of specific manufacturer part numbers. However, it does have the ability to provide a list of alphanumeric generic part numbers (generic parts are defined earlier in this chapter). Once the total number of generic part numbers was known for each functional class, the random number generator in Microsoft Excel's Data Analysis Pak was used to randomly select the generic part numbers for each functional class. This was done by creating a uniform random distribution of numbers from 1 to the n for each functional class, then annotating the nth generic part number from the complete list of generic part numbers for that functional class.

The data was annotated, then keypunched into Microsoft Excel. Using built-in worksheet functions in Excel (i.e., the IF function), the flag colors were converted to both binary and trilevel variables. Another Excel function was used to find the design age based on the time elapsed in years between the datasheet date and 10 July 1999. The only data missing was the voltage for one IC.

A detailed comparison reveals that the sample is very representative of the population. Since the sample was proportionally drawn by function, these chosen strata obviously agree almost perfectly with the presence of each function in the population database. For military specificity, the sample displays nearly the same proportion of military specific IC's as the database, with 21.3% of the sample being military specific versus 23.1% for the database as a whole. Voltage representation in the sample also agreed closely with the population distribution, with both significant groupings in the 3-volt and 5-volt categories appearing in similar proportions in the sample.

The sample also appears to be very representative of the population in terms of technology as well, though a few differences stand out. Most notably, the sample consists of an excess of BICMOS, GAAS, and hybrid based IC's, at 8.1%, 2.1%, and 6.8%, respectively. The population percentages of these technologies were 2.2%, 0.3%, and 2.7%, respectively.

The overrepresentation of these technologies means that some other technologies were underrepresented. The underrepresented technologies were TTL, bipolar, and MOS, at 14.0%, 8.1%, and 2.6%, respectively. The population percentages of these technologies were 16.9%, 11.8%, and 4.0%, respectively.

The representation of technologies by the sample may cause some concern from the standpoint of misrepresenting some DMSMS trends based on differences in technology. However, the distribution is relatively accurate, and the rest of the sample's representation accurately reflects the population.

Statistical Analysis

The principal statistical analysis used to generate the results of this thesis was logistic regression. Logistic regression was chosen because the dependent variable is an indicator variable. This section provides a brief description of logistic regression and its implications.

Though linear regression is a familiar tool for research, when the outcome variable is binary or dichotomous in nature, a logistic regression model seeks to provide the "best

fitting and most parsimonious" model for describing the relationship between the predictor and response variables (Hosmer and Lemeshow, 1989: 1).

Logistic regression measures differences in proportions of the population at each level of the dependent variable as the proportions of each outcome change in relation to one or more predictor or independent variables. The result in many applications (where the dependent variable is dichotomous) is a curvilinear response function described by the logistic distribution. The specific form of the logistic regression model is as follows (Hosmer and Lemeshow, 1989: 6; Neter, et al., 1996: 570):

$$E(Y) = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}} \qquad (1)$$

where

E(Y)=the expected value of the response variable

β0=the intercept parameter

β1=the slope parameter

X=the independent variable

The logistic regression model is transformed into a function that provides many of the desirable qualities of a linear regression model (Hosmer and Lemeshow, 1989: 6; Neter, et al., 1996: 571). The transformed function is linear in its parameters, may be continuous, and can have any range that X can take on from $-\infty$ to $+\infty$.

The formula for the transformation is expressed as a function, *g(x)*. The equation for the function of the transformation is:

$$g(x) = \log_e\left(\frac{E(Y)}{1 - E(Y)}\right) \qquad (2)$$

where

$E(Y)$=the expected value of the response variable from (1)

Logistic regression was chosen to evaluate the binary DMSMS presence of this thesis because it alleviates several concerns with the basic assumptions of the linear regression model. A logistic regression model is a special case of the linear regression model, and the principles that apply to linear regression in general apply to logistic regression as well (Hosmer and Lemeshow, 1989: 6). However, it addresses several problems that arise when the dependent variable is a binary or an indicator variable that linear regression does not suitably address. These problems are: 1) Nonnormal error terms, 2) nonconstant error variance, and 3) constraints on the response function. An excerpt from Neter, et al. discusses each of these problems (Neter, et al., 1996: 569-570):

> Special problems arise, unfortunately, when the response variable is an indicator variable. We consider three of these now, using a simple linear regression model as an illustration.
>
> 1. *Nonnormal Error Terms.* For a binary 0, 1 response variable, each error term $\varepsilon_i=Y_i-(\beta_0+\beta_1 X_i)$ can take on only two values:
>
> (14.5a) When $Y_i=1$: $\varepsilon_i=1-\beta_0-\beta_1 X_i$
>
> (14.5b) When $Y_i=0$: $\varepsilon_i=-\beta_0-\beta_1 X_i$

Clearly, normal error regression model (2.1), which assumes that the ε_i are normally distributed, is not appropriate.

2. *Nonconstant Error Variance.* Another problem with the error terms ε_i is that they do not have equal variances when the response variable is an indicator variable. To see this, we shall obtain $\sigma^2\{Y_i\}$ for the simple linear regression model (14.1), utilizing (A.15):

$$\sigma^2\{Y_i\}=E\{(Y_i-E\{Y_i\})^2\}=(1-\pi_i)^2\pi_i+(0-\pi_i)^2(1-\pi_i)$$

or:

$$\sigma^2\{Y_i\}=\pi_i(1-\pi_i)=(E\{Y_i\})(1-E\{Y_i\}) \tag{14.6}$$

The variance of ε_i is the same as that of Y_i because $\varepsilon_i= Y_i-\pi_i$ and π_i is a constant:

$$\sigma^2\{\varepsilon_i\}=\pi_i(1-\pi_i)=(E\{Y_i\})(1-E\{Y_i\}) \tag{14.7}$$

or:

$$\sigma^2\{\varepsilon_i\}=(\beta_0+\beta_1X_i)(1-\beta_0-\beta_1X_i) \tag{14.7a}$$

Note from (14.7a) that $\sigma^2\{\varepsilon_i\}$ depends on X_i. Hence, the error variances will differ at different levels of X, and ordinary least squares will no longer be optimal.

3. *Constraints on Response Function.* Since the response function represents probabilities when the outcome variable is a 0, 1 indicator variable, the mean responses should be constrained as follows:

$$0 \le E\{Y\}=\pi \le 1 \tag{14.8}$$

Many response functions do not automatically possess this constraint. A linear response function, for instance, may fall outside the constraint limits within the range of the predictor variable in the scope of the model.

The difficulties created by the need for the restriction in (14.8) on the response function are the most serious. One could use weighted least squares to handle the problem of unequal error variances. In addition, with large sample sizes the method of least squares provides estimators that are asymptotically normal under quite general conditions, even if the distribution of error terms is far from normal. However, the constraint on the mean responses to fall between 0 and 1 frequently will rule out a linear response function. In the industrial relations department example, for instance, use of a linear response function subject to the constraints on the mean response might require a probability of 0 for the mean response for all

> small firms and a probability of 1for the mean response for all large firms... Such a model would be considered unreasonable. Instead, a model where the probabilities 0 and 1 are reached asymptotically . . . would usually be more appropriate.

Logistic regression is one model that reaches probabilities 0 and 1 asymptotically. It uses a sigmoidal, or tilted S curve, response function. For the problem of nonnormal error terms, the logistic regression model uses a binomial distribution to describe the distribution of errors. Logistic regression uses binomial errors based on the conditional mean. With the logistic model, the estimates of standard error will have a mean of approximately zero and a variance of approximately one (Hosmer and Lemeshow, 1989: 150).

The problem of constraints on the indicator variable is satisfied by the formulation given in equation 1 above, which limits the response variable to a value between zero and the highest response variable (Hosmer and Lemeshow, 1989: 7).

The output used to evaluate the results of this thesis included the likelihood ratio chi-square test, which corresponds to the F test, and the *p*-value. According to the online software documentation, part of JMP's model fit output is an R-square that is actually an uncertainty coefficient (U). JMP annotates the uncertainty coefficient as R^2 (U), measuring the proportion of total uncertainty attributed to the model fit was also part of the output, which can easily be translated to R-square by taking one minus the R-square of uncertainty (Hosmer, 1989: 148-149; SAS, 1995: 120).

It is important to note that the output of logistic regression is given as a set of probabilities. Given a dependent variable with multiple levels, the logistic function returns

probabilities for each level. Once probabilities are known for each level of the response variable, proportions of the population at each level may also be calculated.

For this research, the two-level DMSMS response variable is modeled using a function that returns the conditional probabilities of the two outcome categories for the given covariate vector.

The trilevel DMSMS presence is modeled using two functions which return the conditional probabilities of each outcome category for a given covariate vector. The generalized forms of the formulae used in this thesis are (as given in Hosmer and Lemeshow, 1989: 218-219):

$$P(Y=0\mid x)=\frac{e^{g_1(x)}}{1+e^{g_1(x)}+e^{g_2(x)}} \tag{3}$$

$$P(Y=1\mid x)=\frac{e^{g_2(x)}}{1+e^{g_1(x)}+e^{g_2(x)}} \tag{4}$$

$$P(Y=2\mid x)=\frac{1}{1+e^{g_1(x)}+e^{g_2(x)}} \tag{5}$$

where

Y=the level of the response variable

x=a value of the independent variable

$g_1(x)$=the logit transformation for the logistic function for a response of 1

$g_2(x)$=the logit transformation for the logistic function for a response of 2

The two functions, $g_1(x)$ and $g_2(x)$ represent the functions of the logit functions for response variable Y=1 versus Y=0, and for Y=2 versus Y=0, respectively. Therefore, the

response of Y=0 becomes the baseline for comparison in the trilevel measurement of DMSMS.

Statistical Software

Three principal software packages were used to process the data and perform the statistical analysis. For data entry and coding, Microsoft Excel was used. After the data was entered into Microsoft Excel, SAS Institute's JMP statistical software package was used to perform the logistic regression modeling. After the models were developed, they were evaluated either in Microsoft Excel or JMP.

Summary

This chapter presented the experimental design used to address the research questions. The independent and dependent variables were chosen based on both theoretical and practical methodological considerations. Data comes from a well-respected technical database and also from manufacturer product datasheets. Though there are some limitations on the sampling, it was found adequate for the purposes of this research.

The method of statistical evaluation is a fairly new but promising variant of simple linear regression called logistic regression. The logistic regression response function has been found to accurately describe biological and business phenomena when the response variable is nominal. The prediction ability of logistic regression returns probabilities for a certain level of the response variable given a value of the predictor variable.

The last two chapters of this thesis attempt to address the hypotheses, and answer the basic research questions as set forth in Chapter I. The goodness of fit of the logistic regression models will form the basis for evaluating these hypotheses, and the hypotheses will form the basis for answering the research questions.

IV. Analysis of Results

Introduction

This chapter details the results of the data analysis. Evaluation of the implications and how the results relate to findings of other research are left for the next chapter.

This chapter presents the results of twenty different logistic regression models are presented. The first five model each of the independent variables against the binary DMSMS response variable. Using the two most significant independent variables, a sixth model was run to assess whether a two-factor model would provide an improved fit. Lastly, based upon the results obtained from the first six models, four models were run to assess possible interactions between the two strongest factors.

The second group of ten models describes the logistic regression modeling of the five independent variables versus the trilevel DMSMS response variable. The same procedures used for the bilevel variable were applied to the trilevel variable.

The last part of the chapter is devoted to identifying the "best" model of the twenty based on model strength and goodness of fit as well as possibilities for practical application.

Logistic Regression Model: Binary DMSMS Presence

In the analysis of the binary DMSMS presence dependent variable using logistic regression, five logistic regression models were tested. The five models were run using the five independent variables individually against the binary DMSMS response variable. In addition, models were run using the two independent variables that demonstrated the

strongest effect strengths versus binary DMSMS response variable. After the presentation of the models, one is chosen as the best binary DMSMS presence logistic regression model based on its fit. After choosing a binary model, its function is used to predict the proportion of IC's out of production for a given value of the independent variable. Then the function line for the predicted proportions of DMSMS afflicted ICs is compared to the actual proportions. A summary of all results is shown in Table 4.

Table 4: Comparison of Model Statistics for Binary DMSMS Presence

Dependent Variables	**Likelihood Ratio Chi-square**	***p*-value**	**R^2 (U)**	**R^2**
Design Age	16.45	0.0000	0.0599	0.9401
Military Specific	14.69	0.0001	0.0578	0.9422
Function	3.08	0.9896	0.0200	0.9800*
Technology	3.63	0.8890	0.0240	0.9760*
Voltage (as a continuous variable	0.74	0.3911	0.0026	0.9974
Voltage (as a nominal variable)	7.80	0.9931	0.0907	0.9093*
Design Age & Military Specific	47.00	<0.0001	0.1475	0.8525

* unstable parameter estimates

Design Age versus Binary DMSMS Presence. Using JMP's logistic regression modeling capability, design age as independent variable and binary DMSMS presence as the dependent variable were modeled. The resulting parameter estimates are an intercept, or β_0, of -1.377, and a slope, or β_1, of 0.117. The complete results of JMP's logistic regression model and its test of hypothesis are summarized in Appendix H.

The test of hypothesis presented by JMP was conducted with an α=0.05, and was a test of H_0: $\beta_1=0$ and H_a: $\beta_1 \neq 0$. The Wald chi-square for design age was 16.45 with a corresponding p-value of <0.0001. This indicates that Design Age has a very strong effect on determining DMSMS presence for this model.

The whole model result was a likelihood ratio chi-square of 19.08 with a corresponding p-value of <0.0001, which is well within α=0.05. Therefore, enough evidence exists to reject H_0: $\beta_1=0$ and accept the alternate hypothesis that our β's are significant to the α=0.05 level. Further support for our model appears in the R^2 (uncertainty) of 0.0599, which reveals that the logistic regression model of design age versus binary DMSMS presence explains 94.01% of the sample variation of the dependent variable.

The evidence is strong that a model of design age versus binary DMSMS presence provides sufficient explanatory power to a significance of α=0.05 to use this logistic regression model in our analysis.

Military Specificity versus Binary DMSMS Presence. Military specific design was modeled as the independent variable with binary DMSMS presence as the response variable. In the model, military specific designs were codified as a 1 while designs that were not military specific were codified as a 0.

The resulting parameter estimates are an intercept, or β_0, of -0.867,and a slope, or β_1, of 0.791. The complete results of JMP's logistic regression model and its test of hypothesis are summarized in Appendix I.

The test of hypothesis presented by JMP was conducted with an α=0.05, and was a test of H_0: $\beta_1=0$ and H_a: $\beta_1 \neq 0$. The result of the effect test on military binary variable returned a Wald chi-square of 14.69 with the p-value of 0.0001. The result of the whole model test was a likelihood ratio chi-square of 18.42 with a corresponding p-value of <0.0001, which is well within α=0.05. Therefore, enough evidence exists to reject H_0: $\beta_1=0$ and accept the alternate hypothesis that our β's are significant to the α=0.05 level. Further support for our model appears in the R^2 (uncertainty) of 0.0578, which reveals that the logistic regression model of design age versus binary DMSMS presence explains 94.22% of the sample variation of the dependent variable.

These results indicate that military specific designs have a strong effect on DMSMS affliction of ICs. The estimate of β_1 is greater than 0.5 (β_1=0.791), which indicates that military designed components tend to stay in production relatively more often than non-military specific ICs. In light of the long-term applications for many military components, these results come as no surprise. The possible importance of the military design independent variable is discussed in more detail both later in this chapter in the analysis of the results of the design age-military design binary model as well as in Chapter V.

Function versus Binary DMSMS Presence. When function was modeled as the independent variable versus binary DMSMS presence, functions were treated as nominal values. The software package (JMP) automatically treated the function names as nominal variables in its assessment of the logistic regression model.

The effect test for function returned a Wald chi-square of 3.085 with a p-value of 0.9896. The whole-model test displayed a correspondingly poor likelihood ratio chi-square

of 6.361 with a p-value of 0.8482. The reason seems to be that not enough ICs for each function were available upon which to build a model. The software returned a warning of "unstable" for each of the functions as well as the intercept, which generally indicates insufficient data for a certain level of the variable. The JMP model appears in Appendix J.

This indicates that our sample size was insufficient to produce an accurate model. Referring to the numbers of each function present in our sample, we can see that seven out of twelve of the functions appeared less than ten times each in the database. The R^2 appears quite good at 0.02, but because the number of parameters is quite high, and there is no adjusted R^2 for logistic regression, this figure is not to be trusted.

In summary, function does not appear to have a strong effect on the binary DMSMS response variable. However, this area may hold promise for future research with a larger sample size.

Technology versus Binary DMSMS Presence. Technology was modeled as a nominal independent variable against the binary DMSMS presence response variable. Because of the multiple levels of technology, results appear somewhat analogous to the model of function versus binary DMSMS presence.

The effect test for technology returned a Wald chi-square of 3.63 with a p-value of 0.8890. The whole model test returned a likelihood ratio chi-square of 7.64 with a p-value of 0.4696. It does not appear based on these summary statistics as if technology has a significant effect on the binary DMSMS response variable. As with the model for function, the R^2 is not to be trusted as technology consists of many parameters, and no adjusted R^2 exists for logistic regression. These results appear in Appendix K.

A couple of the parameter estimates were returned by the software package as "unstable," indicating that for those technologies, insufficient number of ICs for those technologies were included in the sample upon which to base any accurate statistical inferences. These technologies were DTL and ECL, which only appeared once and twice respectively in the sample.

We already noted that the representation of each technology in the sample set was somewhat less than balanced. The results of the logistic regression model based on technology seems to support that a larger sample may provide a stronger statistical basis for model building, as it should provide both a more representative sample and more data at each level.

Overall, the current model indicates that the technology variable does not seem to contribute significant information for predicting binary DMSMS presence. A topic for future investigation could entail gathering additional data in order to investigate further the relationship between technology and binary DMSMS presence.

Voltage versus Binary DMSMS Presence. Voltage was modeled twice. The first model treated voltage as a continuous variable while the second model treated voltage as a nominal variable. The models give quite different results but are included in the same section because of the low statistical significance of the model treating voltage as a continuous variable.

For voltage treated as a continuous independent variable, the results of JMP's analysis appear in Appendix L. The effect test on voltage gives a Wald chi-square of 0.735 and a p-value of 0.3911. The whole model test gave a likelihood ratio chi-square of 0.820

and a p-value of 0.3651. Overall, the effect test and whole model test indicate a weak relationship between voltage as a continuous variable and the binary DMSMS presence response variable.

When treated as a category (see JMP's results in Appendix M), the effect test for voltage against binary DMSMS presence indicated virtually no relation at all with a Wald chi-square of 7.798 and a p-value of 0.9931. The parameter estimates for voltage were all unstable, indicating that as categories the voltages do not contain enough representation at each level from which to derive significant statistical inference. So, even though the whole model test appears quite good with a likelihood ration chi-square of 28.789 and a p-value of 0.0920, it is not to be trusted without additional data to support the model. The large number of parameters also prevents us from relying on the R^2 (uncertainty) of 0.0907.

It appears that voltage probably does not have much influence on the presence of binary DMSMS for ICs. Additional research into the different voltage standards as the IC voltage standard continues to fall may provide additional insight into the unstable relationship indicated by the model of voltage treated as a nominal variable, but for this thesis no strong relationship was found.

Design Age and Military Specificity versus Binary DMSMS Presence. Military specificity and design age were both included in the same model as the independent variables with binary DMSMS presence as the response variable. In this model, as in the previous models, military specific designs were codified as a one while designs that were not military specific were codified as a zero. Design age was left as a continuous variable.

The resulting parameter estimates are an intercept of -1.3562. The slope for the military variable is -2.1101, while the slope for the design age is 0.1589. These results are summarized in Appendix N.

The test of hypothesis presented by JMP was conducted with an α=0.05, and was a test of H_0: $\beta_1=\beta_2=0$ and H_a: $\beta_1\neq\beta_2\neq0$. The result of the whole model test was a likelihood ratio chi-square of 26.0799 with a corresponding p-value of <0.0001, which is well within α=0.05. Therefore, enough evidence exists to reject H_0: $\beta_1=\beta_2=0$ and accept the alternate hypothesis that our β's are significant to the α=0.05 level.

Further support for our model somewhat diminishes with an R^2 (uncertainty) of 0.1475, which reveals that the logistic regression model of design age and military specificity versus binary DMSMS presence explains only 85.25% of the sample variation of the dependent variable. This indicates a lower explanatory power for this model compared to the individual models of military design and design age against binary DMSMS presence, which had R^2's of 0.9422 and 0.9401, respectively. This seems to indicate the possible presence of interaction, but this topic is discussed in detail in the next section.

The Binary DMSMS Presence Interactive Models: Design Age and Military Specificity. Since the non-interactive two-factor model of design age and military specificity displayed low R^2 compared to the single factor models of each of these factors, it was decided to test for interaction.

The dataset was partitioned so that both military and non-military were modeled separately against design age. This approach allowed for identification of any possible differences in DMSMS trends for military and non-military designed ICs, and thereby

isolates the interaction, while still providing a conceptually parsimonious model. Then, in order to analyze the full effects of any interaction for both factors, the dataset was also divided according to design age.

For the 50 military ICs, it is interesting to note that the lowest design age was 3.58 years. This is consistent with the three year acquisition cycle identified in the literature review. The oldest design age was 22.53 years.

The logistic regression model for design age only the military ICs versus the design age appears in Appendix O and is summarized in Table 6. The effect test for the logistic regression model for design age modeled against the 50 military ICs demonstrated a Wald's chi-square of 3.31 and a p-value of 0.0688. The whole model test demonstrated a likelihood ratio chi-square of 3.37 and a corresponding p-value of 0.0663. The R^2 for the whole model was 0.9233; this seems to indicate a strong logistic regression model for the relationship of the binary DMSMS response to design age for military ICs.

Even stronger results appeared in the logistic regression model of design age versus binary DMSMS response for the non-military ICs (refer to Appendix P). The effect test returned values of 19.34 for the Wald's chi-square and <0.0001 for the p-value. The whole model test calculated a 25.26 likelihood ratio chi-square and a p-value of <0.0001. The R^2 for the whole model test was 0.9014%. The number of non-military ICs in the sample was 185.

Up to this point it appeared as if there were indeed different aging trends for military versus non-military ICs with regard to their design age. This begged the question of

whether this remained true no matter the design age of IC in question, which leads to the second half of the interaction analysis, the division of the dataset by design age.

Table 5: Comparison of Interactive Model Statistics

	Military Specificity 0	Military Specificity 1
Design Age	Observations: 185 Chi-square*: 25.26 *p*-value: <0.0001 R^2: 0.9014	Observations: 50 Chi-square*: 3.37 *p*-value: 0.0663 R^2: 0.9233

	Design Age Low (≤8.110 years)	Design Age High (>8.110 years)
Military Specificity	Observations: 119 Chi-square*: 8.13 *p*-value: 0.0043 R^2: 0.9421	Observations: 116 Chi-square*: 0.33 *p*-value: 0.5660 R^2: 0.9979

* Likelihood ratio chi-square

As seen in Appendix E, the distribution of design ages approximated a lognormal distribution. Therefore it seemed most appropriate to divide the database based on the median design age value. The median value of design age was 8.11 years. Since there were four ICs with the median design age of 8.11 years, it was arbitrarily decided to include the four median values in the lower set of design ages. This produced a dataset of lower design age ICs consisting of 119 both military and non-military ICs.

A logistic regression model of the lower design ages including both military and non-military ICs was very strong. Referring to Appendix Q, the effect test for design age for the lower design ages returned a Wald chi-square of 7.40 with a *p*-value of 0.0065. The whole model test likelihood ratio chi-square was 8.13 with a *p*-value of 0.0043 with an R^2 of

0.9421. This indicates that for younger ICs, there is a very strong relationship for design age predicting the binary DMSMS response for both military and non-military ICs.

On the other hand, the model for the higher design ages for military and non-military ICs, based on the remaining 116 ICs, demonstrated a lot of variance. Analysis for this model appears in Appendix R. The effect test Wald chi-square was 0.043 with a p-value of 0.5689. The whole model test returned a likelihood ratio chi-square of 0.33 with a p-value of 0.5660. The R^2 is a very good 0.9879. This indicates that our other factor, military specificity, causes a significant difference in behavior for the military ICs versus the non-military ICs as design age becomes greater.

A look at all four of these models identifies an important difference in the binary DMSMS presence among ICs. These models provide strong evidence that earlier in the lives of ICs, as indicated by their design ages, there is little detectable difference in binary DMSMS presence for military and non-military ICs. However, as the ICs become older, the military ICs stay in production far longer than the non-military ICs. This comes as no surprise given the history of long production lives for military equipment, much of which depends on ICs.

The "Best" Logistic Regression Model for Binary DMSMS Presence. A comparison of the logistic regression models for the dependent binary DMSMS presence variable presents some difficult choices for choosing the "best" model. Observed significance levels and R^2 values are quite good for some of the models, though not for others, as summarized on Table 3.

From the viewpoint of explanatory ability as indicated by R^2, all models appear quite good. However, the observed significance levels of each of the effects (the *p*-values) leads to the conclusion that only design age and military specificity have a statistically significant relationship with binary DMSMS presence based on the evidence of these models.

Looking at the result of the models analyzing for interaction, it appears that at least for older design ages, looking at separate models for military and non-military ICs may prove beneficial for predicting binary DMSMS presence. Table 4 summarizes the results of the models for interaction.

Three of the interactive models appear quite robust. The fourth model, which models older design ages for both military and non-military ICs, indicates a lot of variability. The interpretation of these results is that design age has a strong, measurable effect on binary DMSMS presence, but military ICs DMSMS behavior diverges from the behavior of DMSMS for non-military ICs as the design age increases.

This indicates that from the military's point of view of managing vital IC components, important information can be gained by separately analyzing military versus non-military ICs. As military ICs age, monitoring how much they differ from the commercial IC trends in DMSMS may provide insights into feasibility of continuing production. This possibility is discussed more thoroughly in Chapter V.

Based on model strength and applicability to the research questions, as well as applicability to Air Force logistics management, the "best" binary DMSMS presence logistics regression model will actually be the two models for design age versus the separate military and non-military ICs.

Implementing the Design Age Binary DMSMS Presence Model. The design age versus binary DMSMS presence logistics regression model function, when transformed with the logit function, returns the probability for a specified age that the response variable is a one, or still has at least one manufacturer. Using the separate models for military and non-military ICs, the expressions for these models would be:

For military ICs:

$$E(Y \mid x) = -3.2577 + 0.1420x \qquad (6)$$

For non-military ICs:

$$E(Y \mid x) = -1.3851 + 0.1626x \qquad (7)$$

where: Y=binary DMSMS response variable
x=design age independent variable

The maximum design age in the sample set was 22.53 years; therefore, the analysis of this section uses a range of 0 through 23 years for design age.

Based on the logit transformation of the logistic function using the estimated parameters, a chart was created displaying the predicted probabilities of no manufacturers for an IC. The calculated probabilities for no manufacturers can be seen as a rather shallow upward trend as the design age increases. As can be seen, at age zero (according to the model) only about 4% of IC's go out of production. After nearly 23 years, only half of the military ICs are out of production. An overlay of the actual proportion of out of production ICs reveals that in the most general sense the model reflects the sample.

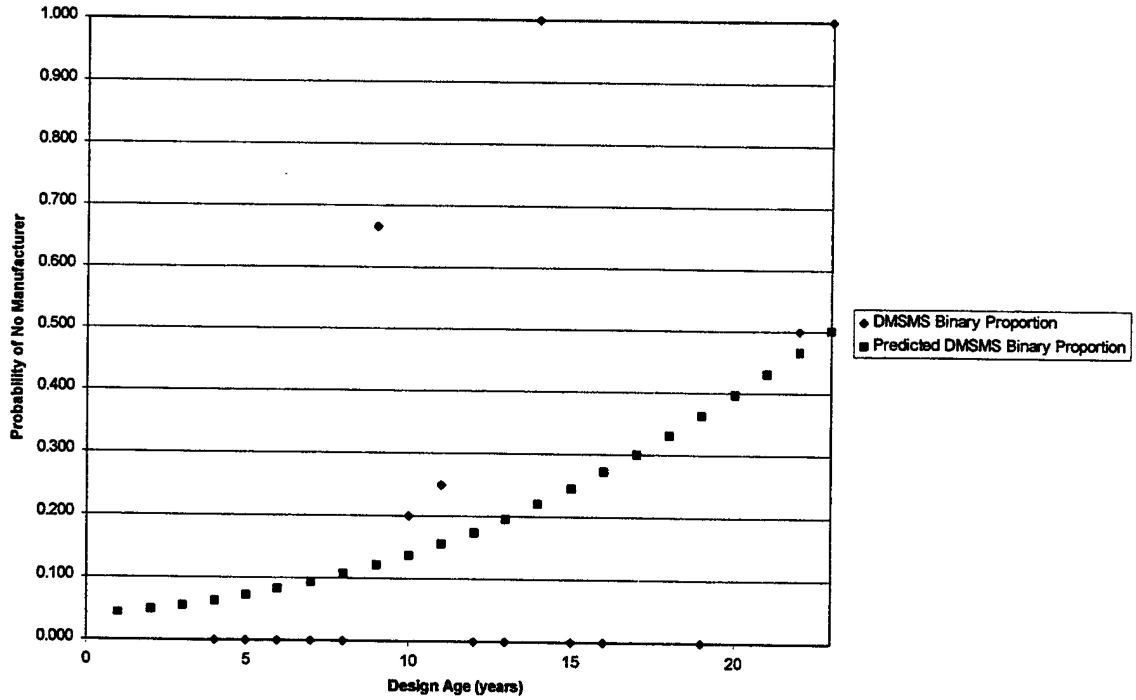


Figure 1: Probability of No Manufacturers for Given Design Ages for Military ICs

The logistic regression of the model for military ICs provides powerful insight when compared to the model for non-military ICs. The range of design ages used to produce the chart went from 0 to 31, in accordance to the maximum 30.54 years design age present in the sample. Looking at Figure 2, a visual comparison of the overlaid actual proportions of no manufacturers by design age reveals that the predicted line seems a reasonable fit.

Comparing the non-military and military models, non-military ICs appear to have a much shorter production life. Fifty percent of the ICs have no manufacturers after about only nine years. Compared to the 23-year predicted age at which half of military ICs have no manufacturers, this difference is quite large.

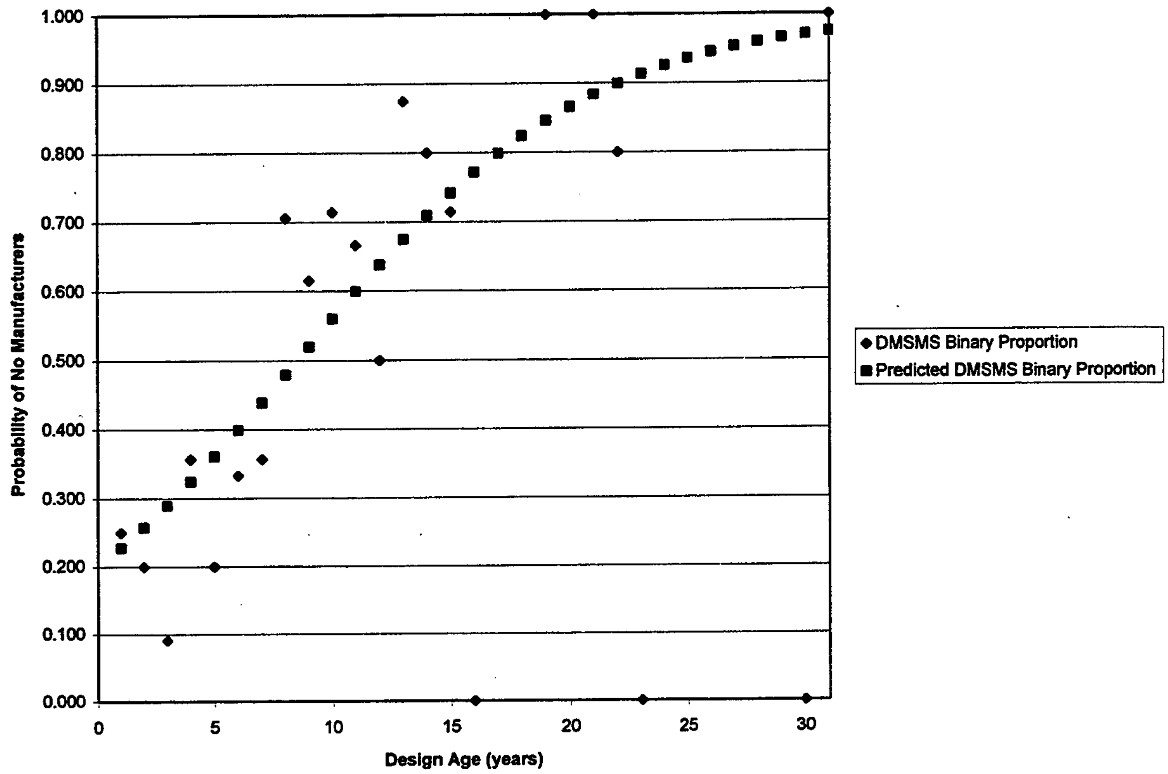


Figure 2: Probability of No Manufacturers for Given Design Ages for Non-Military ICs

After deciding on the "best" model, it is appropriate to use it to address the research questions. The separate models for military and non-military ICs seems an accurate predictor of binary DMSMS presence for ICs. As a tool, these models also need to be assessed for their ability to contribute to answering the research questions.

Logistic Regression Model: Trilevel DMSMS Presence

In the analysis of the trilevel DMSMS dependent variable using logistic regression, five logistic regression models were tested. The five models were run using the five independent variables individually against the trilevel DMSMS response variable. In addition, models were run using the two independent variables that demonstrated the strongest effect strengths versus trilevel DMSMS response variable.

Table 6: Comparison of Model Statistics for Trilevel DMSMS Presence

Dependent Variables	**Likelihood Ratio Chi-square**	***p*-value**	**R^2 (U)**	**R^2**
Design Age	30.72	<0.0001	0.0639	0.9361
Military Specific	30.07	<0.0001	0.0625	0.9375
Function	31.56	0.0852	0.0656	0.9344*
Technology	27.70	0.0343	0.0576	0.9424*
Voltage (as a continuous variable	0.99	0.6086	0.0021	0.9979
Voltage (as a nominal variable)	46.47	0.2231	0.0970	0.9030*
Design Age & Military Specific	65.11	<0.0001	0.01354	0.8646

* unstable parameter estimates

After the presentation of the models, one is chosen as the best trilevel DMSMS presence logistic regression model based on its fit and parsimony. After choosing a trilevel DMSMS presence model, its function is used to predict the proportion of IC's out of production for a given value of the independent variable. Then the function line for the predicted proportions of DMSMS afflicted ICs is compared to the actual proportions.

Design Age versus Trilevel DMSMS Presence. Using JMP's logistic regression modeling capability, design age as independent variable and trilevel DMSMS presence as the dependent variable were modeled. The results of logistic regression for a two level response variable are two functions that describe the probability of an IC corresponding to a certain response level based upon its design age. The software calculations for this model appear in Appendix S.

The parameter estimates for the function describing the probability of a response level of zero (a red flag, or no manufacturers in existence) were an intercept of 0.6464 and a slope of 0.02919. The parameter estimates for the function describing the probability of a response level of one (a yellow flag, or more than one manufacturer in existence) were an intercept of 2.1024 and a slope of -0.1432.

The tests of hypothesis presented by JMP was conducted with an α=0.05, and was a test of H_0: $\beta_1=0$ and H_a: $\beta_1 \neq 0$ for both functions using the estimated parameters (see Table 7). For the response level zero regression model function, the effect test on design age returned a Wald chi-square of 0.67 and a p-value of 0.4137. For the response level one regression model function, the effect test on design age returned a Wald chi-square of 26.95 and a p-value of 0.0007. The result of the whole model test was a likelihood ratio chi-square of 30.7227 with a corresponding p-value of <0.0001, which is well within α=0.05. Therefore, enough evidence exists to reject H_0: $\beta_1=0$ and accept the alternate hypothesis that our β's are significant to the α=0.05 level. Further support for our model appears in the R^2 (uncertainty) of 0.0639, which reveals that the logistic regression model of design age

versus binary DMSMS presence explains 93.61% of the sample variation of the dependent variable.

These results seem quite good in light of the complexity of the model. The evidence is strong that design age provides sufficient explanatory power to a significance of α=0.05 that this logistic regression model accurately portrays the proportions of IC population corresponding to each of the response levels based on design age.

However, the effect test for the response level of zero, or no manufacturers still producing the IC, is quite weak. The *p*-value of only 0.4137 indicates that predicting which ICs have only one manufacturer is statistically difficult, especially compared to the excellent results of the test for ICs that have no producers.

However, the overall model strength indicates that it is still quite reliable for making predictions. The question of how useful this model is for predicting DMSMS is addressed later in the chapter when all the trilevel DMSMS presence models are assessed for the best fitting.

Military Specificity versus Trilevel DMSMS Presence. Military specific design was modeled as the independent variable with trilevel DMSMS presence as the response variable. In the model, military specific designs were codified as a one while designs that were not military specific were codified as a zero. As with the model of design age and trilevel DMSMS presence, the model consists of two functions describing the borders between the three response levels.

The resulting parameter estimates for a response level of zero, or no manufacturers in existence for an IC, are an intercept, or β_0, of 1.5983, and a slope, or β_1, of -2.5146. The

resulting parameter estimates for a response level of one, or only one manufacturer in existence for an IC, are an intercept, or β_0, of 1.4663, and a slope, or β_1, of -1.3710. The complete results of JMP's logistic regression model and its test of hypothesis are summarized in Appendix T.

The test of hypothesis presented by JMP was conducted with an $\alpha=0.05$, and was a test of H_0: $\beta_1=0$ and H_a: $\beta_1\neq 0$. The effect test for military design for response level of one returned a Wald chi-square of 26.15 and a p-value of <0.0001. The effect test for military design for response level of two returned a Wald chi-square of 11.47 and a p-value of 0.0007.

The result of the whole model test was a likelihood ratio chi-square of 30.0702 with a corresponding p-value of <0.0001, which is well within $\alpha=0.05$. Therefore, enough evidence exists to reject H_0: $\beta_1=0$ and accept the alternate hypothesis that our β's are significant to the $\alpha=0.05$ level. Further support for our model appears in the R^2 (uncertainty) of 0.0625, which reveals that the logistic regression model of design age versus trilevel DMSMS presence explains 93.75% of the sample variation of the dependent variable.

It seems that there is a strong relationship between whether an IC is designed for the military and its longevity as demonstrated by the trilevel DMSMS response variable and design age. This model indicates that for military ICs, the probability of no manufacturers is far lower than it is for non-military ICs. This relationship was seen in the binary DMSMS response variable models, and its importance in relation to the trilevel DMSMS response

variable later in this chapter in the section discussing the "best" trilevel logistics regression model.

Function versus Trilevel DMSMS Presence. The logistic regression model for function versus trilevel DMSMS presence revealed an effect test for function with a Wald chi-square of 11.3191 and a p-value of 0.9699. This seems to indicate that function is a poor predictor of the trilevel DMSMS response variable. These results appear in Appendix U.

For the whole model test of function versus the trilevel DMSMS presence response variable, the likelihood ratio chi-square was 31.56006, with a p-value of 0.0852. However, every parameter for both levels of the response variable is unstable, indicating that more data is needed to arrive at a statistically significant model. With unstable parameter estimates and a p-value greater than 0.05, this model does not exhibit any statistical significance.

Technology versus Trilevel DMSMS Presence. The logistic regression model for technology versus trilevel DMSMS presence revealed an effect test for technology with a Wald chi-square of 11.2633 and a p-value of 0.7929 (reference Appendix V). This seems to indicate that technology is a very poor predictor of the trilevel DMSMS response variable.

For the whole model test of technology versus the trilevel DMSMS presence response variable, the likelihood ratio chi-square was 27.70107, with a p-value of 0.0343. A look at the parameter estimates shows that every parameter was unstable. Not enough data points at each level were present in the sample to provide a reliable statistical model of technology as a predictor of trilevel DMSMS presence.

As with the model of function versus trilevel DMSMS presence, the R^2 is an unreliable measure of the model's usefulness. Since logistic regression has no adjusted R^2, more data is needed to build a better case that function indeed provides no insight into trilevel DMSMS presence.

Voltage versus Trilevel DMSMS Presence. Voltage was modeled as both a continuous and a nominal variable. Results for both models follow.

Modeling voltage as a continuous variable, the logistic regression model for voltage versus trilevel DMSMS presence revealed an effect test for voltage with a Wald chi-square of 0.8188 and a *p*-value of 0.6640 (reference Appendix W). This seems to indicate that voltage as a continuous variable is a very poor predictor of the trilevel DMSMS response variable.

For the whole model test of voltage as a continuous variable versus the trilevel DMSMS presence response variable, the *p*-value was 0.6086. This indicates that voltage as a continuous variable does not exhibit statistical significance for modeling the trilevel DMSMS presence response variable.

When modeling voltage as a nominal variable (refer to Appendix X), the effect test returned a Wald chi-square of 12.2394 with a corresponding *p*-value of 1. This indicates no relationship at all exists between voltage and trilevel DMSMS presence.

For the whole model test of voltage as a nominal variable versus the trilevel DMSMS presence response variable, the likelihood ratio chi-square was 46.47483, with a *p*-value of 0.2231. However, a look at the parameter estimates shows that every parameter

was unstable. Not enough data points at each level were present in the sample to provide a reliable statistical model of voltage as a predictor of trilevel DMSMS presence.

As with the model of function versus trilevel DMSMS presence, the R^2 is an unreliable measure of the model's usefulness. Since logistic regression has no adjusted R^2, more data is needed to build a better case that function indeed provides no insight into trilevel DMSMS presence.

The weak relationship between voltage and trilevel DMSMS presence is somewhat surprising in light of the concern that changing trends in voltage standards among ICs have caused. This may be explained by the fact that in the sample, over 85% of the ICs fall into two categories of voltage, the 3 to 3.3-volt ICs and the 5-volt ICs. A large enough sample to provide sufficient numbers of the newer, lower voltage ICs as well as the older, higher voltage ICs may lead to quite different results. That is a recommendation for future research.

Design Age and Military Specificity versus Trilevel DMSMS Presence. A third model was created in which military specificity and design age were both included as the independent variables with trilevel DMSMS presence as the response variable. In this model, as in the previous models, military specific designs were codified as a 1 while designs that were not military specific were codified as a 0. Design age was left as a continuous variable.

The results of the model indicate a high observed significance level for this model. The test of hypothesis presented by JMP was conducted with an α=0.05, and was a test of H_0: $\beta_1=\beta_2=0$ and H_a: $\beta_1\neq\beta_2\neq 0$. The results (summarized in Appendix Y) were a chi-

square of 65.1146 with a corresponding p-value of <0.0001, which is well within $\alpha=0.05$. Therefore, based on the observed significance level, enough evidence exists to reject H_0: $\beta_1=\beta_2=0$ and accept the alternate hypothesis that our β's are significant to the $\alpha=0.05$ level.

However, further support for our model diminishes with an R^2 (uncertainty) of 0.1354, which reveals that the logistic regression model of design age and military specificity versus binary DMSMS presence explains 86.46% of the sample variation of the dependent variable.

The strong results of the separate military specificity and design age models but a relatively weaker model of both indicates that perhaps there is some interaction. The results of the binary DMSMS models lend strong support to this possibility. The possibility of interaction is explored in the next section.

The Trilevel DMSMS Presence Interactive Models: Design Age and Military Specificity. Since the non-interactive two factor model of design age and military specificity displayed lower R^2 values compared to the single factor models of each of these factors, it was decided to test for interaction.

Since the interactive component of design age and military specificity would effectively eliminate all zero-valued military ICs, or the non-military ICs, it seemed logical to divide the dataset so that both military and non-military were modeled separately by design age. This approach allowed for identification of any possible differences in DMSMS trends for military and non-military designed ICs, and thereby isolates the interaction, while still providing a conceptually parsimonious model. Then, in order to analyze the full effects of any interaction for both factors, the dataset was also divided according to design age.

Table 7: Comparison of Interactive Model Statistics for Trilevel DMSMS Presence

Design Age	Military Specificity: 0	Military Specificity: 1
	Observations: 185 Chi-square*: 28.58 *p*-value: <0.0001 R^2: 0.9181	Observations: 50 Chi-square*: 6.57 *p*-value: 0.0374 R^2: 0.9356

Military Specificity	Design Age: Low (≤8.110 years)	Design Age: High (>8.110 years)
	Observations: 119 Chi-square*: 9.80 *p*-value: 0.0074 R^2: 0.9555	Observations: 116 Chi-square*: 0.34 *p*-value: 0.8438 R^2: 0.9985

* Likelihood ratio chi-square

The logistic regression model for design age only the military ICs versus the design age appears in Appendix Z. The effect test for the logistic regression model for design age modeled against the 50 military ICs for a response level of zero demonstrated a Wald's chi-square of 1.12 and a *p*-value of 0.2908. The effect test for the logistic regression model for design age modeled against the 50 military ICs for a response level of one demonstrated a Wald's chi-square of 2.85 and a *p*-value of 0.0913. Design age appears to have a strong effect on military ICs for predicting a response level of one, but not for predicting a response level of zero.

The whole model test demonstrated a likelihood ratio chi-square of 6.57 and a corresponding *p*-value of 0.0374. The R^2 for the whole model was 0.9356; this seems to indicate a strong logistic regression model for the relationship of the trilevel DMSMS response to design age for military ICs.

Similar results appeared in the logistic regression model of design age versus trilevel DMSMS response for the non-military ICs (refer to Appendix AA). The effect test for the logistic regression model for design age modeled against the 185 non-military ICs for a response level of zero demonstrated a Wald's chi-square of 2.08 and a p-value of 0.1494. The effect test for the logistic regression model for design age modeled against the non-military ICs for a response level of one demonstrated a Wald's chi-square of 18.53 and a p-value of 0.0903. The R^2 for this model was 0.9181, indicating a quite useful measure for our model, but with questionable statistical significance.

It appears as if there are indeed different DMSMS trends for military versus non-military ICs with regard to their design age.

As with the interaction test under the bilevel DMSMS response variable, the database was split based on the median design age value. The median value of design age was 8.11 years. Since there were four ICs with the median design age of 8.11 years, it was arbitrarily decided to include the four median values in the lower set of design ages. This produced a dataset of lower design age ICs consisting of 119 both military and non-military ICs.

Logistic regression models of the lower design ages comparing military and non-military ICs were equally weak. Referring to Appendix BB, the effect test for design age for the lower design ages for a response level of zero returned a Wald chi-square of 0.88 with a p-value of 0.3471. The effect test for design age for the lower design ages for a response level of one returned a Wald chi-square of 1.62 with a p-value of 0.2025. These indicate statistically insignificant models for the lower design ages on the trilevel DMSMS response.

The whole model test likelihood ratio chi-square was 9.80 with a *p*-value of 0.0074 and an R^2 of 0.9555. This indicates that for younger ICs, the logistic model is a very strong predictor for design age predicting the trilevel DMSMS response for both military and non-military ICs.

The model for the higher design ages for military and non-military ICs, based on the remaining 116 ICs, demonstrated a lot of variance. Analysis for this model appears in Appendix CC. The effect test for the response level of zero returned a Wald chi-square of 0.14 with a p-value of 0.7119. The whole model test returned a likelihood ratio chi-square of 0.01 with a p-value of 0.9190. No inferences can be drawn from these models.

A look at all four of these models seems to identify an important difference in the trilevel DMSMS presence among ICs. These models provide strong evidence that earlier in the lives of ICs, as indicated by their design ages, there is little detectable difference in trilevel DMSMS presence for military and non-military ICs. However, as the ICs become older, the military ICs stay in production far longer than the non-military ICs. This comes as no surprise given the history of long production lives for military equipment, much of which depends on ICs. These trilevel DMSMS results are entirely consistent with the bilevel results.

The "Best" Logistic Regression Model for Trilevel DMSMS Presence. The logistic regression models for the trilevel DMSMS presence response variable demonstrate varying observed significance levels, as summarized on Table 5.

From the viewpoint of explanatory ability as indicated by R^2, all models appear quite good. However, the observed significance levels of each of the effects (the *p*-values) leads

to the conclusion that only design age and military specificity have a detectable relationship with trilevel DMSMS presence based on the evidence of these models.

Looking at the result of the models analyzing for interaction, it appears that at least for older design ages, looking at separate models for military and non-military ICs may prove beneficial for predicting trilevel DMSMS presence. Table 6 summarizes the results of the models for interaction.

Three of the interactive models appear quite robust. The fourth model, which models older design ages for both military and non-military ICs, indicates a lot of variability. The interpretation of these results is that design age has a strong, measurable effect on binary DMSMS presence, but military ICs DMSMS behavior diverges from the behavior of DMSMS for non-military ICs as the design age increases.

This indicates that from the military's point of view of managing vital IC components, important information can be gained by separately analyzing military versus non-military ICs. As military ICs age, monitoring how much they differ from the commercial IC trends in DMSMS may provide insights into feasibility of continuing production. This possibility is discussed more thoroughly in Chapter V.

Based on model strength and applicability to the research questions, as well as applicability to Air Force logistics management, the "best" binary DMSMS presence logistics regression model will actually be the two models for design age versus the separate military and non-military ICs.

Implementing the Design Age Trilevel DMSMS Presence Model. The design age versus trilevel DMSMS presence logistics regression model functions, when transformed

with the logit function, return the probabilities for specified levels of trilevel DMSMS presence given different ages. The expressions for the proportions of the populations expected at each of the three levels of DMSMS are as follows:

$$P(Y=0\,|\,x)=\frac{e^{g_1(x)}}{1+e^{g_1(x)}+e^{g_2(x)}} \qquad (7)$$

$$P(Y=1\,|\,x)=\frac{e^{g_2(x)}}{1+e^{g_1(x)}+e^{g_2(x)}} \qquad (8)$$

$$P(Y=2\,|\,x)=\frac{1}{1+e^{g_1(x)}+e^{g_2(x)}} \qquad (9)$$

where: Y=the response variable

x=the design age

The two functions, $g_1(x)$ and $g_2(x)$, represent the probability functions for a response level of zero or one, respectively, given a design age. The generalized forms of these functions with the estimated parameters are:

$$g_1(x)=-1.9647+0.08761x \qquad (10)$$

$$g_2(x)=1.3963-0.1353x \qquad (11)$$

where: x=the design age

In the analysis of the model, we based design age values in the range of the military IC subsample. The maximum design age in the sample set was 22.53 years; therefore, the analysis of this section uses a range of 0 through 23 years for design age.

Based on the logit transformation of the logistic function using the estimated parameters, three charts were created, each displaying the predicted probabilities of no manufacturers, one manufacturer, or more than manufacturer for a military IC.

The calculated probabilities for no manufacturers can be seen in Figure 3 as a rather shallow upward trend as the design age increases. As can be seen, at age zero only about 4% of IC's go out of production. After nearly 23 years, only half of the military ICs are out of production. An overlay of the actual proportion of out of production ICs reveals that in the most general sense the model reflects the sample.

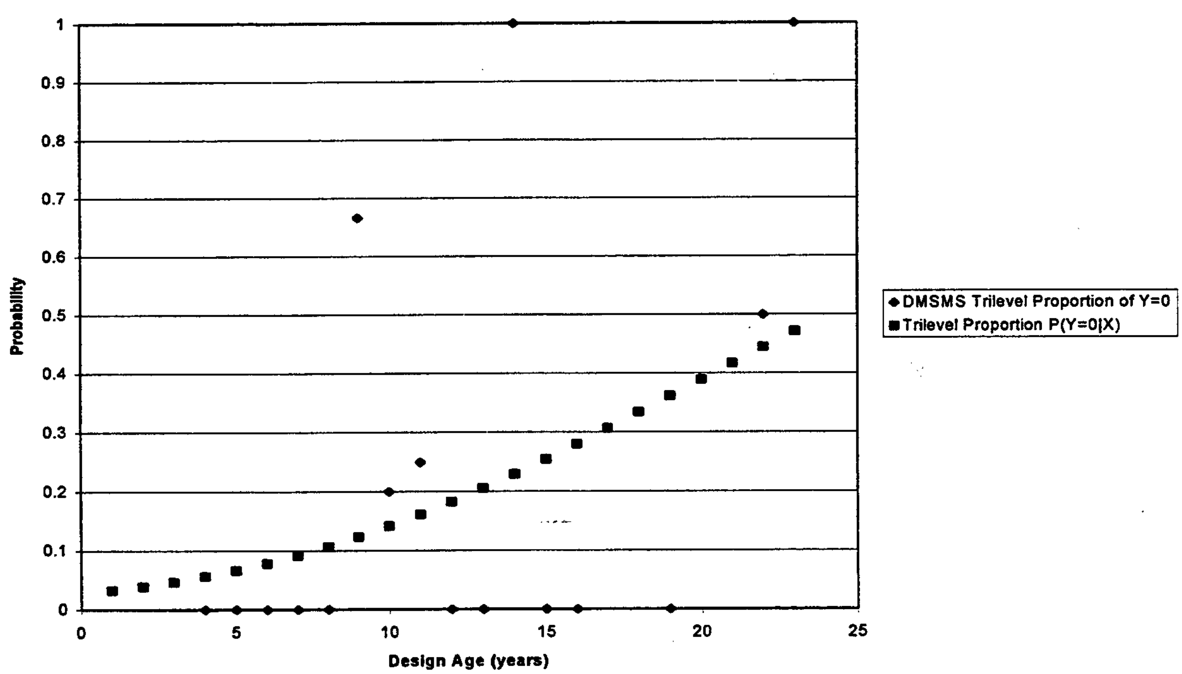


Figure 3: Predicted and Actual Proportions for Military ICs with No Manufacturers

The graph for predicted and actual response level of one for military ICs, or the military ICs with only one manufacturer, reveals a downward sloping line that starts to flatten out after 20 years of design age. This can be seen in Figure 4. There are few datapoints for visually assessing the fit between the predicted and actual data.

The graph for predicted and actual response level of two for military ICs, or the military ICs with more than one manufacturer, reveals an upward sloping line that starts to flatten out after 15 years of design age. This can be seen in Figure 5. There are few datapoints for visually assessing the fit between the predicted and actual data.

The logistic regression of the model for military ICs provides powerful insight when compared to the model for non-military ICs. The range of design ages used to

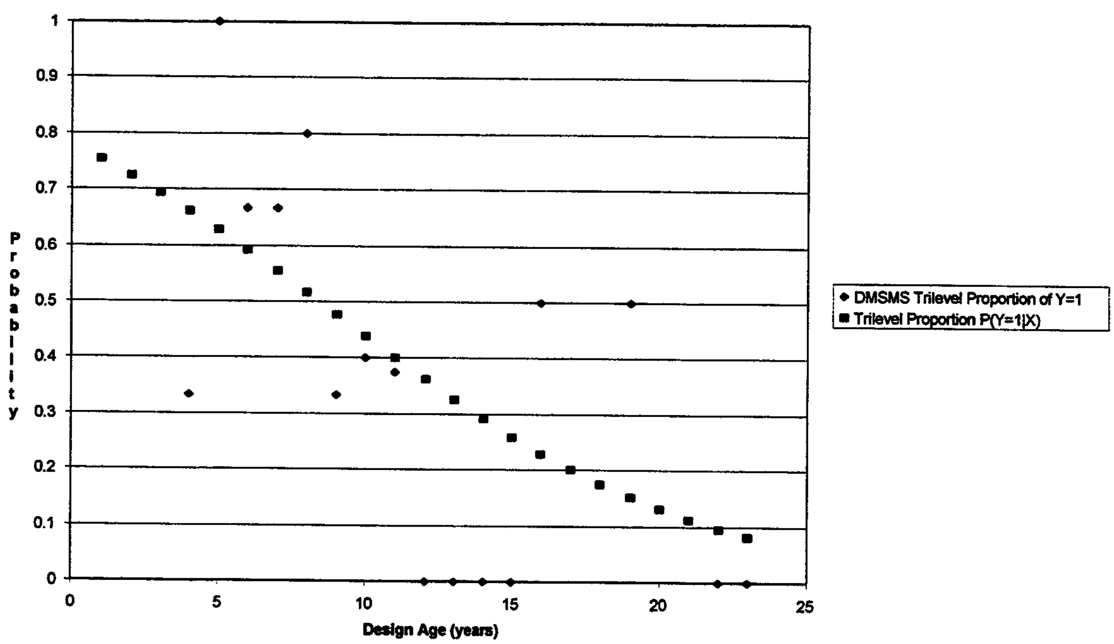


Figure 4: Predicted and Actual Proportions for Military ICs with One Manufacturer

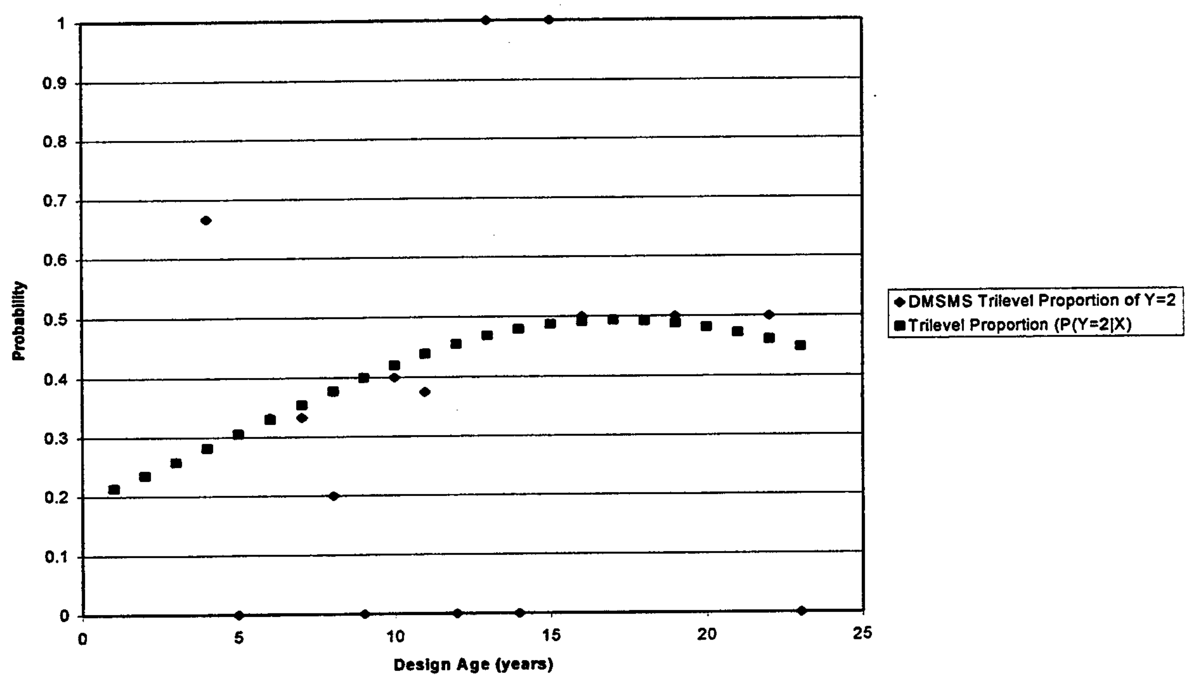


Figure 5: Predicted and Actual Proportions for Military ICs with More than One Manufacturer

produce the chart went from 0 to 31, in accordance to the maximum 30.54 years design age present in the sample. Looking at Figure 6, a visual comparison of the overlaid actual proportions of no manufacturers by design age reveals that the predicted line seems a very good fit. It slopes upward sharply, starting with over 20% of non-military ICs with no manufacturers in the first year and begins to flatten out at about 20 years with approximately 85% of non-military ICs with no manufacturers.

For non-military ICs with only one manufacturer, the design age model appears to be another tight fit. As seen in Figure 7, the prediction line slopes downward sharply, with less ICs having exactly one manufacturer as the IC ages. At one year, about 70% of the ICs have a single manufacturer, but this quickly drops to about 15% after 15 years.

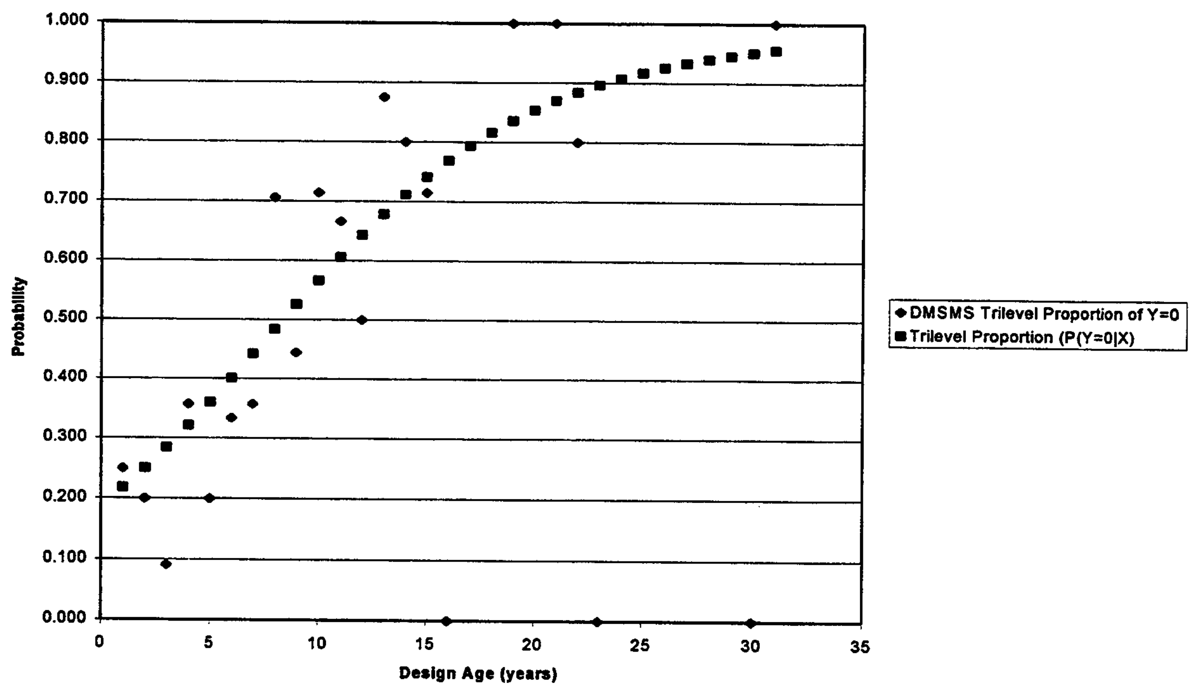


Figure 6: Predicted and Actual Proportions for Non-Military ICs with No Manufacturers

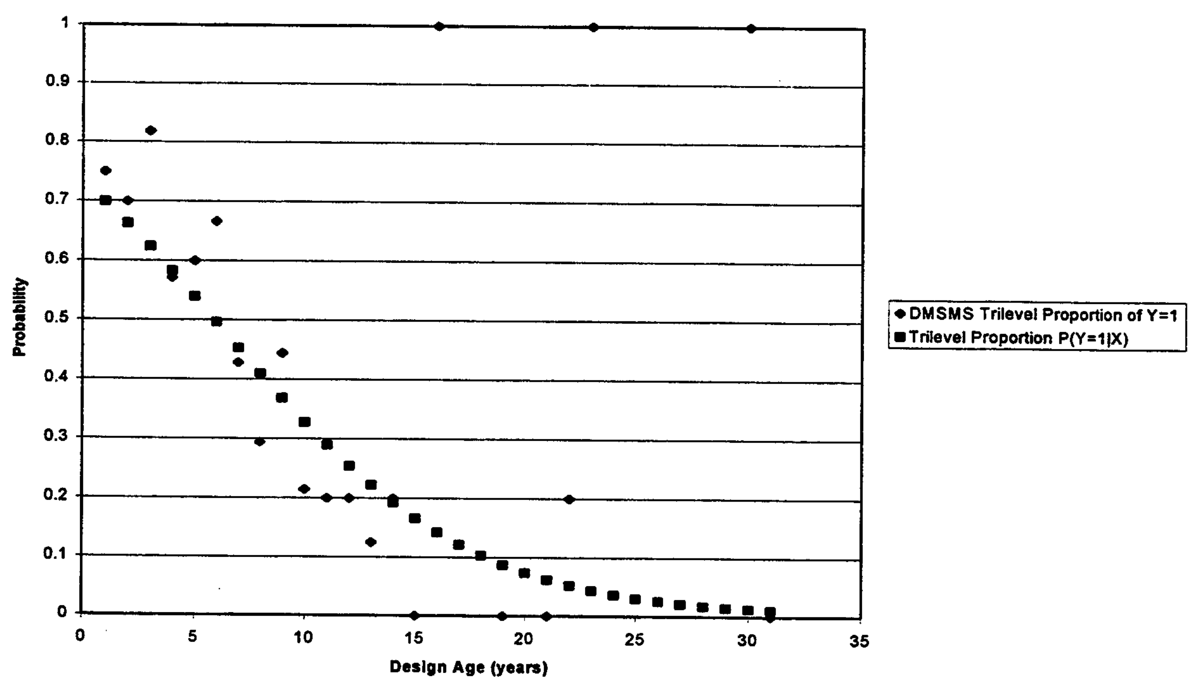


Figure 7: Predicted and Actual Proportions for Non-Military ICs with One Manufacturer

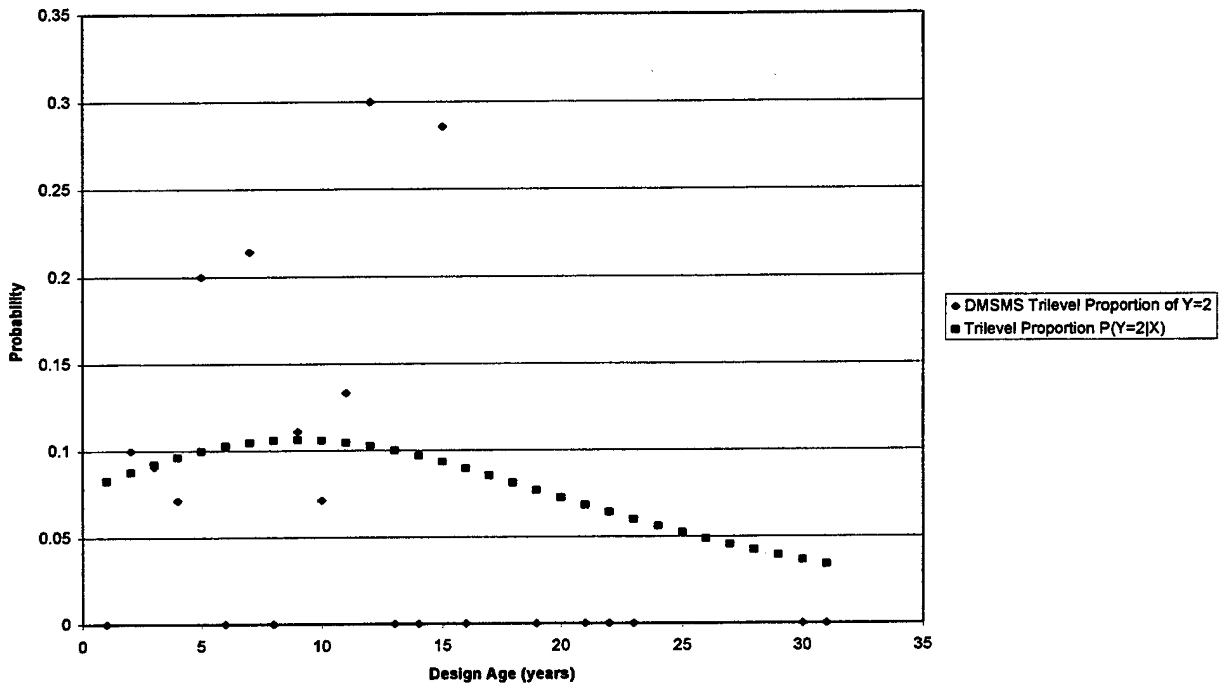


Figure 8: Predicted and Actual Proportions for Non-Military ICs with More than One Manufacturer

For non-military ICs with more than two manufacturers, the actual and predicted lines do not match. As a matter of fact, visual inspection of Figure 8 reveals that the actual plotted data points do not form an identifiable line. The predicted line rises a little for the first 10 years of design age, then drops sharply. At no time does the function predict more than about 11% of non-military ICs will have more than one manufacturer.

It appears that logistic regression does provide accurate information about the proportions of ICs that suffer varying levels of DMSMS presence. The models work for military and non-military separated data, as well as for both military and non-military ICs together in the same database. The trilevel models may not provide as reliable information for use in prediction of varying levels of DMSMS because of the increased number of response levels being predicted.

Answers to Research Questions

Having derived a statistically sound approach to using logistic regression to model binary DMSMS presence, the next step in this thesis is to use this approach to answer the research questions. The research questions all correspond to a hypothesis, in some cases with several research questions answerable with one hypothesis. Each of these hypotheses is addressed using the logistic regression DMSMS presence models as follows.

Research Questions 1 - 3. The first three research questions deal with the applicability of statistical modeling in a general sense. If DMSMS is a totally random occurrence, then no characteristics will form an identifiable pattern of DMSMS presence among ICs. These questions are directed toward the basic research concept of whether DMSMS can be identified or measured according to identifiable IC characteristics.

- Is there a pattern to the characteristics of DMS afflicted versus non-afflicted parts?
- What characteristics form this pattern?
- How much does each of these characteristics affect obsolescence?

H_0: A regression model can not be used to relate DMSMS presence to parts characteristic(s).
H_a: A regression model can be used to relate DMSMS presence to parts characteristic(s).

Due to the strong evidence for all the models of design age and military specificity versus both of the DMSMS response variables, the evidence supports the use of a regression model to relate DMSMS presence to parts characteristics. Therefore, we reject the null and

accept the alternate hypothesis that a regression model can be used to relate DMSMS presence to parts characteristics.

Which characteristics form the basis for the successful regression models answer the first and second research questions. For the first question, about whether there is a pattern to the characteristics of DMS afflicted versus non-afflicted parts, the pattern seems to be that as ICs age, they have fewer manufacturers, regardless of other characteristics. Due to the weak results of the models of technology, function, and voltage, additional research needs done to affirm that these factors do not have an effect on DMSMS presence, but design age and military specificity seem to exert a powerful effect on DMSMS presence.

Though the primary characteristic for determining DMSMS presence seems to be design age, the pattern of DMSMS differs for military and non-military ICs. Military ICs do not suffer from a problem of no manufacturers to nearly the same degree as non-military ICs. One would expect this result based on the premise that the military has a powerful incentive to keep older ICs in production to support its aging weapon systems.

How much design age affects DMSMS presence depends on which range of design ages are being analyzed. The logistic distribution accurately describes the relationship between the design age and DMSMS presence. Drawing from the results of the binary DMSMS presence models, for non-military ICs, half of ICs are out of production in less than nine years. It takes well over 20 years for half of the ICs to have no manufacturers for military ICs.

With such strong evidence that a logistic regression accurately describes the relationship between design age and DMSMS presence for ICs, especially when separated

into military and non-military categories, this hypothesis and its three related research questions have a firm answer.

Research Question 4. If the answers to research questions 1 through 3 indicate that there is a discernible pattern, then research question 4 is the attempt to try to make use of the pattern in a practical sense. If prediction can be accomplished, then DMSMS management comes much closer to being a science.

- Can we use this discernible pattern (if there is one) to make predictions about the degree of DMS afflicting a part?

H_0: The regression model cannot make predictions regarding DMSMS presence for a part.
H_a: The regression model can make predictions regarding DMSMS presence for a part.

To address whether this research provides enough evidence to reject the null, we need to define what is meant by making predictions for "a part." The logistic regression model gives conditional probabilities for a certain level of the response variable based on a given level of the independent variable. This conditional probability can also be interpreted as the expected population proportion to have the level of the response variable under study.

What this means is that for an individual IC, the models presented in this thesis only give probabilities based on design ages. The models presented here are most useful when applied to management of a population of ICs, such as a system comprised of many ICs. The logistic regression models can be used to assess how many ICs will go out of production in the next five years for example. If the design ages of the individual ICs are known, then the model can be used to identify those ICs that are most in danger of going out of production within a system. In this way, logistics managers can ensure that the high-risk

ICs receive aggressive attention to prevent a lost manufacturing source or replace the IC before the manufacturer(s) cease producing it.

As long as the user applies this thesis' logistic regression model in the proper fashion, then the strength of the models supports rejecting the null hypothesis and concluding that the regression models can make predictions regarding DMSMS presence.

Research Question 5. The current pace of technology development is unparalleled in human history. A basic concern when studying development of technology is its ephemeral nature. This question address the concern that technology may cause the model to become obsolete just as quickly as the ICs.

- How applicable is this research in the event a new technology becomes available?

  H_0: The regression model cannot be used in the event of the introduction of a new technology.
  H_a: The regression model can be used in the event of the introduction of a new technology.

This question and hypothesis are fraught with hidden dangers. Obviously, the current trend of accelerated technological development could possible produce some new IC technology that would quickly replace all commonly used technologies. However, assuming that trends in IC production continue, and that new technologies usually require years to develop and pervade the market, it seems safe to address this hypothesis based on the logistic regression models developed for this thesis.

Since technology did not have any measurable impact on DMSMS presence, the models in this thesis provide sufficient evidence to reject the null and accept the alternate

hypothesis that the regression model can be used in the event of the introduction of a new technology. However, given the unstable parameter estimates because of the small sample representation for certain kinds of technologies, additional research may further elucidate this question in the future.

Research Question 6. Even in the event that statistical modeling seems possible, in may be impractical. Since little research exists that identifies which characteristics relate to DMSMS, and therefore which characteristics should appear in DMSMS databases, then existing databases may not even contain the information needed to analyze and predict DMSMS. This question addresses this issue.

- Do current databases provide sufficient information to make predictions on DMS prevalence?

  H_0: Existing databases do provide sufficient information to make predictions about DMSMS presence.
  H_a: Existing databases do not provide sufficient information to make predictions about DMSMS presence.

The most important predictors of DMSMS presence turned out to be design age and military specificity. CAPSXpert and PARTSXpert are an indispensable tools for finding technical data, product datasheets, and tracking the number of manufacturers for ICs. However, though the CAPSXpert database provides an abundance of technical data to the user, including whether the design is military specific, design age was only accessible via a link to the product datasheets. The user must open each product datasheet individually and manually search for the date of publication.

Because the design age is not accessible in an organized, searchable fashion, there is sufficient evidence to reject the null hypothesis and accept the alternate hypothesis that existing databases do not provide enough information to make predictions regarding DMSMS.

What this means in practical terms for logistics managers is that managing DMSMS for ICs becomes a labor-intensive endeavor of searching manufacturer product datasheets for the original design age of each individual IC. Most managers currently do not receive staffing for this type of endeavor. Including this additional information in the database would greatly facilitate the manager's ability to forecast DMSMS for his systems.

Summary and Conclusions

The answers to the research questions indicate that the logistic regression models developed for this thesis provide a powerful tool for managing DMSMS presence. Properly applied, these models can help identify the high-risk ICs in electronic systems. The model functions, once entered into a spreadsheet, are easy to use. And best of all, determining the risk of DMSMS presence depends on knowing only two factors easily determinable over the Internet: design age and military specificity.

The difficulty posed by these models resides in the inaccessibility of design age via database search functions. All design ages must be found and handled individually. Development of a database that tracks both these factors by part number would greatly facilitate use of these models for DMSMS management for ICs. The next chapter addresses

the research questions from the viewpoint of more generalizable conclusions, as well as the possibility of additional future research.

V. Conclusions and Recommendations

Summary of Findings

The current status of integrated circuit (IC) diminishing sources of manufacture is one of rapid obsolescence caused in part by diminished demand for the older parts. The military depends on the continued production of obsolescing IC's in order to sustain its primary weapon systems. The Air Force is particularly hard hit by IC diminishing manufacturing sources and material shortages (DMSMS) due to the heavy reliance of its aircraft on electronics technology.

In answer to the research questions, the findings of this thesis indicate that logistic regression modeling of DMSMS among ICs does identify a pattern for certain characteristics as they relate to DMSMS rates. Logistic regression modeling of IC obsolescence measured by proportions of the populations of ICs that have been discontinued reveals that two variables provide strong predictors of obsolescence. Based on the sample used for this thesis, Design Age and whether the IC was a Military Specific design can be used to create a statistically significant logistic regression model. When modeling DMSMS as a binary variable (either it is out of production or it is not), a whole-model test *p*-value of <0.0001 and an R^2 of 0.0599 indicate that logistic regression provides an accurate model.

For a binary model of without regard to Military Specificity DMSMS, because the variable of interest is a categorical or nominal output, the output of the model provides a conditional probability of obsolescence. In the case of using design age to predict the binary DMSMS response variable, the conditional probability curve reveals that ICs start out with

only about a 2% probability of being out of production in the first year of design age. After just under 14 years of design age half of ICs have no manufacturers. At 30 years of design age, which is close to the average age of the military aircraft fleet, ICs have a 0.89 conditional probability of having no manufacturers. Summaries of the conditional probabilities for no manufacturers, along with a 95% confidence interval for the conditional probability, appear in Table 8.

Analysis also revealed for the binary DMSMS output variable that whether the IC was designed for military specific use had a statistically significant effect on the binary DMSMS response. Since military specificity by itself offers limited practical ability for predicting the probability of DMSMS for an IC, further investigation ensued to answer the question of whether military designed ICs behaved differently than non-military ICs with regards to design age in relation to DMSMS.

When separate models are analyzed for the design ages of military and non-military ICs, the results indicate that military ICs demonstrate a different relationship between design age and the binary DMSMS response. The obsolescence curve rises much less steeply for military ICs compared to non-military ICs, indicating that military ICs stay in production far longer than non-military ICs (refer to Figure 9).

In addition, since obsolescence seems to depend heavily on design age while having little relation to other variables such as process technology or technical characteristics, the model should be applicable even in the event of a change in IC technology.

Table 8: Conditional Probabilities of No Manufacturers (Binary Model)

		Confidence Interval	
Years of Design Age	Prob(Y=0|X)	Lower Bound 95%	Upper Bound 95%
0	0.977365	0.9208582	1.0338725
1	0.948193	0.8916854	1.0046998
2	0.917432	0.8609243	0.9739387
3	0.885171	0.828664	0.9416783
4	0.851531	0.7950236	0.9080379
5	0.81666	0.7601526	0.873167
6	0.780736	0.7242291	0.8372435
7	0.743964	0.6874569	0.8004713
8	0.706569	0.6500617	0.7630761
9	0.668793	0.6122856	0.7253
10	0.630888	0.5743811	0.6873954
11	0.593112	0.5366044	0.6496188
12	0.555716	0.4992087	0.612223
13	0.518944	0.4624369	0.5754513
14	0.483023	0.4265161	0.5395305
15	0.448159	0.3916518	0.5046662
16	0.414531	0.3580238	0.4710382
17	0.382291	0.3257835	0.4387979
18	0.351559	0.2950521	0.4080664
19	0.322427	0.2659202	0.3789346
20	0.294956	0.238449	0.3514634
21	0.269179	0.2126715	0.3256859
22	0.245102	0.1885952	0.3016096
23	0.222712	0.1662052	0.2792196
24	0.201974	0.1454672	0.2584816
25	0.182838	0.126331	0.2393454
26	0.165241	0.1087338	0.2217481
27	0.14911	0.092603	0.2056174
28	0.134367	0.0778595	0.1908739
29	0.120927	0.0644198	0.1774341
30	0.108705	0.0521983	0.1652126
31	0.097616	0.0411091	0.1541235

One problem with measuring DMSMS turned out to be the acquisition of data for determining design ages. While current databases contain a plethora of technical characteristics for ICs, design age can only be accessed by manually searching through

product datasheets. With a small addition to the database, this additional and vital information could be included for DMSMS management purposes.

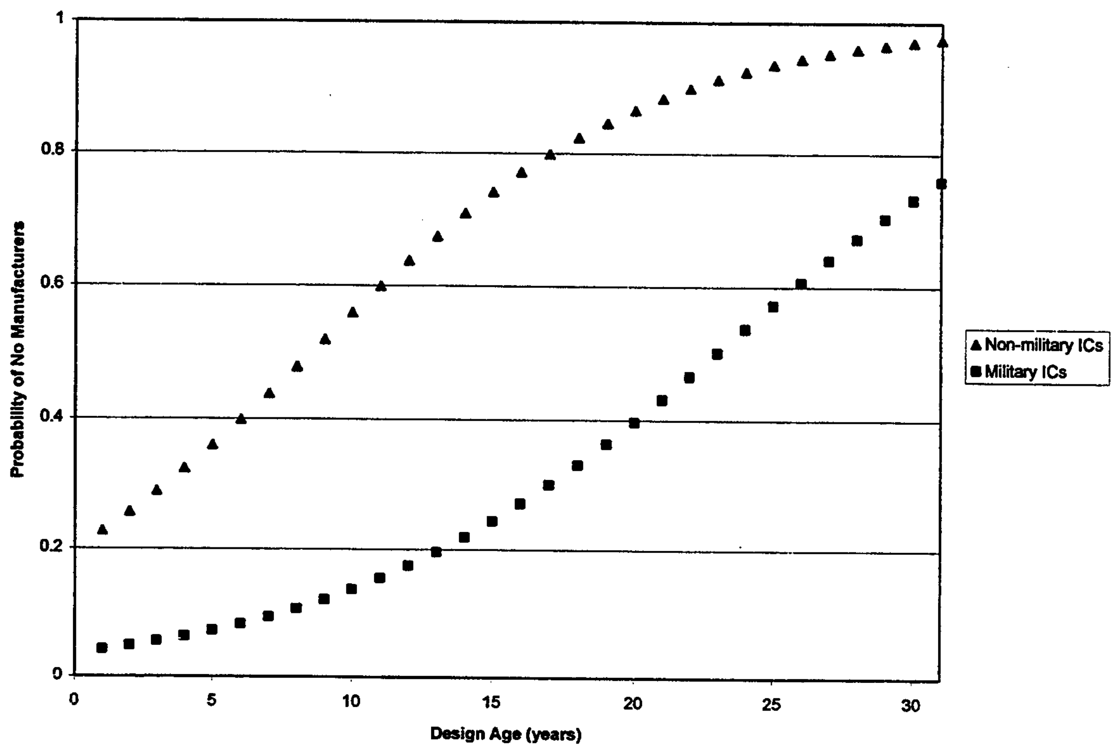


Figure 9. Predicted Proportions for Non-Military and Military ICs

Implications of Findings

The strong findings of this thesis have important implications for the management of DMSMS for ICs. Bell's thesis (Bell, 1998) found that DMSMS among ICs can be managed through a proactive and aggressive policy. The logistic regression model provides a valuable tool to measure the likelihood for each of the ICs that it will be out of production, given its design age and military specificity.

The most important implication of these findings lies in the very different relationships of design age to DMSMS status for military and non-military ICs. The longer production life of military ICs implies that they are funded beyond the point of economic feasibility. When one also considers the small portion of the IC market dedicated to the military, this in turn implies that the military probably has large expenses to keep outdated ICs in production.

Another important implication of this research is that with a desktop computer and spreadsheet software, a manager can calculate conditional probabilities for ICs in a system under evaluation. The information needed to predict these conditional probabilities does not require often costly technical database services since the product datasheets used to derive the design ages are available for free. These product datasheets either come from the manufacturer (in the case of the non-military ICs) or from a military supply center (in the case of the military ICs).

However, the databases that track manufacturer availability do not provide information useful for predicting DMSMS, they still provide invaluable information for actual IC production status. And the addition of design age information in the databases would greatly relieve the workload that accompanies manually pulling the product datasheets. Furthermore, databases could include the conditional probability for no producers as a kind of information on DMSMS risk that would guide prospective use in newly designed systems. A high probability of no producers would imply that the designers might want to consider using another IC.

The fact that the design engineer databases often do not provide the age of an IC implies that designers do not know the age of an IC when it is considered for use in a newly designed system. This could be an explanation for Bell's findings (Bell, 1998) that newly designed systems are not immune to DMSMS. If even a small number of ICs, or even a single key IC, goes out of production, the sustainability of the entire system may be at risk. The logistic regression model provides a means of assessing risk of obsolescence for individual ICs.

When using the logistic regression predictions to assess the risk or probability of an IC going out of production, it is important to remember that there are no guarantees. Constant vigilance of manufacturing status is needed. Also, in the sample some ICs went out of production in as little as half a year. Newer ICs have no guarantee of staying in production. In a world of constantly evolving technology, DMSMS is a problem that will not go away.

Recommendations for Action

Based on this research several recommendations seem appropriate for improving the management of DMSMS among ICs. First, DMSMS managers need to realize that obsolescence can be modeled using statistically valid methods. DMSMS is not an entirely random occurrence. It depends heavily on the design age and the military specificity of the IC. Knowing these two characteristics of an IC provide valuable insight into the relative risk involved for an IC to go out of production. Newly designed systems as well as upgrade

and modification efforts should evaluate the age of ICs at the lowest level in order to proactively identify those ICs with a high risk of going out of production.

Another recommendation is that DMSMS managers, and specifically the Air Force, should strive to have design age information included in the existing databases for ICs. This is a vital piece of information missing from the databases. It was also the most important factor for predicting the conditional probability of DMSMS for ICs.

Since the Air Force exhibits particular concern for DMSMS among ICs, it has a vested interest in cultivating an in-house capability for evaluating DMSMS in its weapon systems. DMSMS among ICs imposes itself upon the Air Force because ICs are the height of technology in its weapons systems. As long as technology is a core competency of the Air Force, the Air Force needs to keep constant vigilance over the systems and components upon which its technology depends so heavily. If the Air Force does not cultivate a program to monitor the status of its technology and ensure its supremacy, the Air Force will eventually lose its technological superiority.

Lastly, this problem does not confine itself to Air Force weapon systems. All the military services rely on ICs to provide technological superiority in weapons as the world's only superpower. This means that in order for a program to be truly effective at minimizing the impact of DMSMS, the Department of Defense needs to become involved in directing the management of DMSMS. This is especially true in light of the move towards more joint weapon systems, including programs such as the Joint Strike Fighter. The technological leadership of the United States military depends on the ability of all the services to "do more with less." Consolidating weapons systems means that more information needs to be shared

between the services in order to avoid wasteful duplication of effort between programs. Also, the failure of this research to find differences in DMSMS patterns based on any factor other than age implies that a single DMSMS research effort would yield benefits for all the services. Also, a Department of Defense-wide program would yield benefits for all the services without putting any single service in the position of spending its limited resources on research while rival services reap the benefits.

Only by judicious planning and consolidated effort can the United States military hope to maintain its military weapons systems as the pinnacle of technology while minimizing the costs accrued due to obsolescence. DMSMS is a problem that benefits from proactive management, and this management depends on research and statistical methods similar to those used in this thesis.

Recommendations for Further Research

Several areas are available for further research in the area of modeling DMSMS. To start with, the model indicate by this thesis needs validated by another research effort modeling design age and military specificity against DMSMS presence. This would be a prerequisite to any additional research using the logistic regression model analyzed in this thesis.

Furthermore, several characteristics require additional research for their importance to evaluating and predicting DMSMS. Among the characteristics for which insufficient data were present in this thesis' sample are technology, voltage, die size, and function. While design age and military specificity provide statistically significant indicators for predicting

the conditional probabilities of no manufacturers for ICs, other factors may still contribute information valuable for improving the accuracy of statistical modeling of DMSMS.

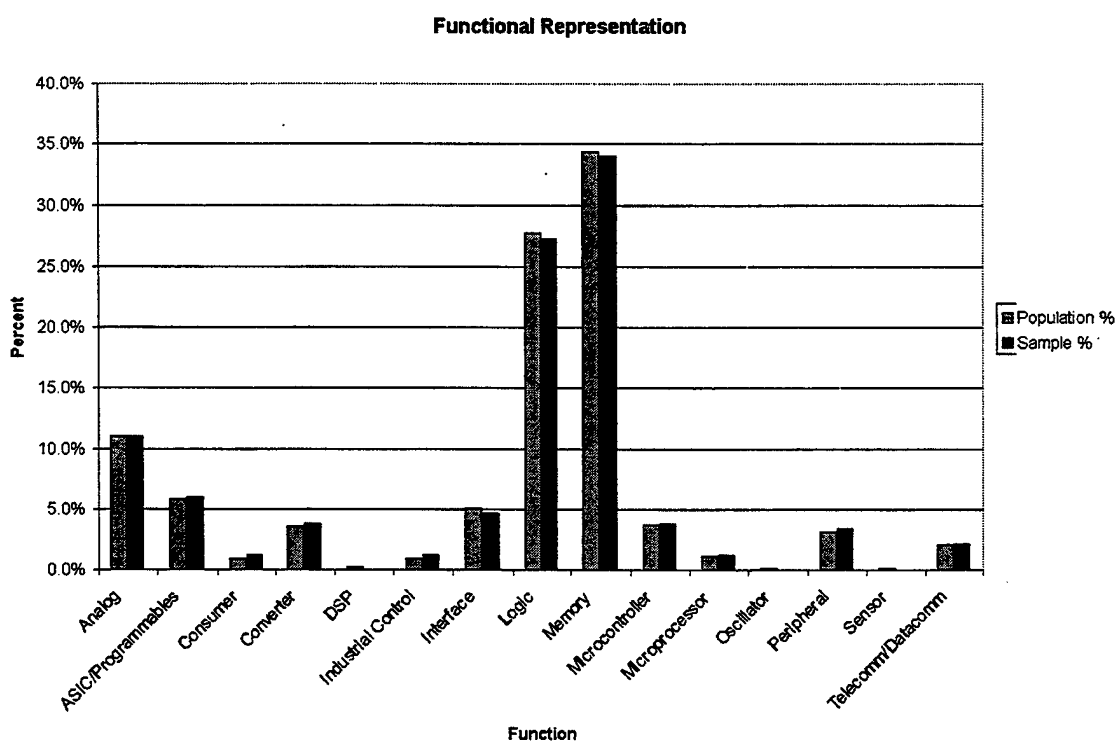
A comparison between logistic regression modeling of DMSMS presence and the methods used by DMSMS companies such as Manufacturing Technologies, Inc. (MTI) to forecast DMSMS may yield additional insight into DMSMS behavior. Time series data for MTI's predictions versus actual DMSMS presence compared to the logistic regression model's ability to predict conditional probabilities of DMSMS presence would indicate which method provides greater accuracy and usability for DMSMS management.

Another area where this research effort may provide a powerful contribution is for cost and benefit analysis in electronic system design. The probabilities for an individual IC to go out of production may be useful if combined with cost data for acquiring or continuing production of the IC in order to evaluate the lowest most likely cost for a system design strategy. Additional research is needed to evaluate the feasibility of combining cost modeling with DMSMS modeling.

In conclusion, statistical modeling of DMSMS presence is not only possible, but with easily accessible data becomes quite practicable. The benefits of being able to statistically evaluate DMSMS presence extend to the areas of designing new systems and upgrading and modifying existing systems. Most important of all, statistical modeling of DMSMS would give DMSMS-managers control over the fate of their systems. Development of an accurate statistical model would mean the difference between having to wait for DMSMS to appear and charging out to attack it.

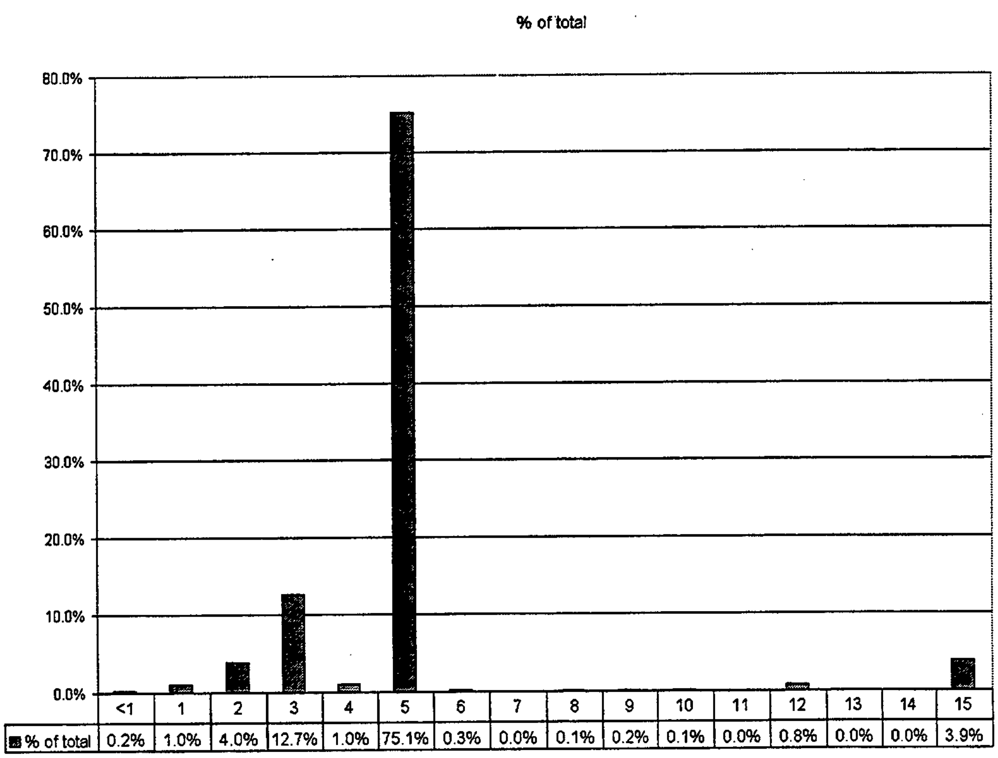
Appendix A: Representation by Function

Function	n	Population %	Sample frequency	Sample %
Analog	85,550	11.0%	26	11.1%
ASIC/Programmables	44,999	5.8%	14	6.0%
Consumer	7,133	0.9%	3	1.3%
Converter	27,788	3.6%	9	3.8%
DSP	1,854	0.2%	N/A	N/A
Industrial Control	7,019	0.9%	3	1.3%
Interface	39,339	5.1%	11	4.7%
Logic	215,648	27.7%	64	27.2%
Memory	267,219	34.4%	80	34.0%
Microcontroller	28,848	3.7%	9	3.8%
Microprocessor	9,047	1.2%	3	1.3%
Oscillator	1,311	0.2%	N/A	N/A
Peripheral	24,390	3.1%	8	3.4%
Sensor	1,248	0.2%	N/A	N/A
Telecomm/Datacomm	15,885	2.0%	5	2.1%
Total	**777,278**		**235**	
% of database (777,278)	100.0%		0.0302%	



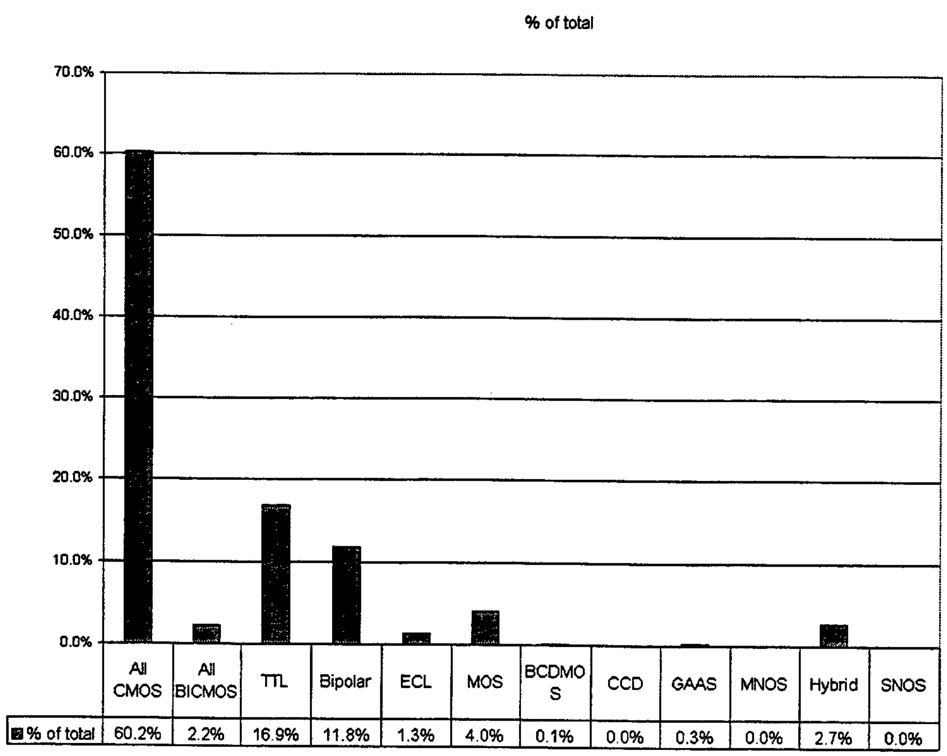
Appendix B: Representation by Voltage

Voltage	n	% of total	sample frequency	sample %
<1	1,583	0.2%	0	0.0%
1	6,670	1.0%	5	2.1%
2	26,729	4.0%	7	3.0%
3	85,793	12.7%	36	15.4%
4	6,840	1.0%	1	0.4%
5	507,102	75.1%	164	70.1%
6	1,762	0.3%	0	0.0%
7	317	0.0%	1	0.4%
8	965	0.1%	1	0.4%
9	1,223	0.2%	0	0.0%
10	915	0.1%	0	0.0%
11	59	0.0%	1	0.4%
12	5,239	0.8%	4	1.7%
13	186	0.0%	3	1.3%
14	232	0.0%	2	0.9%
15	26,519	3.9%	2	0.9%
16+	3,032	0.4%	7	3.0%
Total n	**675,166**		**234**	
% of database	86.9%			



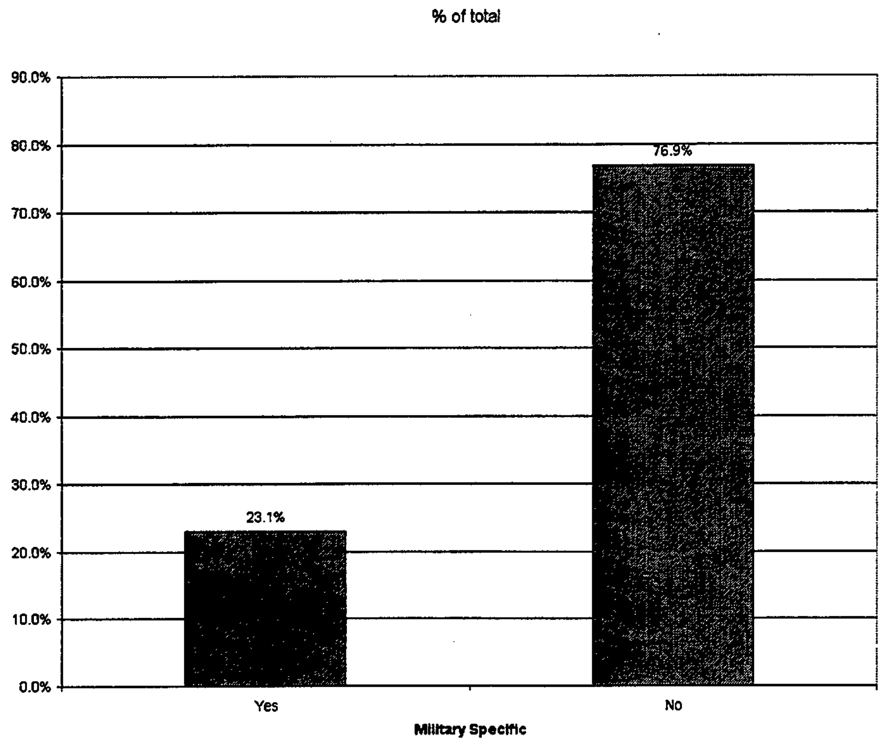
Appendix C: Representation by Technology

Technology	n	% of total	Sample frequency	% of sample
All CMOS	465,528	60.2%	134	57.0%
All BICMOS	17,172	2.2%	19	8.1%
TTL	130,263	16.9%	33	14.0%
Bipolar	90,985	11.8%	19	8.1%
ECL	10,224	1.3%	2	0.9%
MOS	31,148	4.0%	6	2.6%
BCDMOS	581	0.1%	0	0.0%
CCD	15	0.0%	0	0.0%
GAAS	2,249	0.3%	5	2.1%
MNOS	177	0.0%	0	0.0%
Hybrid	21,129	2.7%	16	6.8%
SNOS	80	0.0%	0	0.0%
BTL	23	0.0%	0	0.0%
DTL	2,390	0.3%	1	0.4%
HNIL	602	0.1%	0	0.0%
I2L	243	0.0%	0	0.0%
JFET	16	0.0%	0	0.0%
Total n	**772,825**		**235**	
% of database	99.4%			



Appendix D: Representation by Military Specificity

Military	n	% of total	sample
Yes	165003	23.1%	21.3%
No	548010	76.9%	78.7%
Total n	**713013**		
% of database	91.7%		

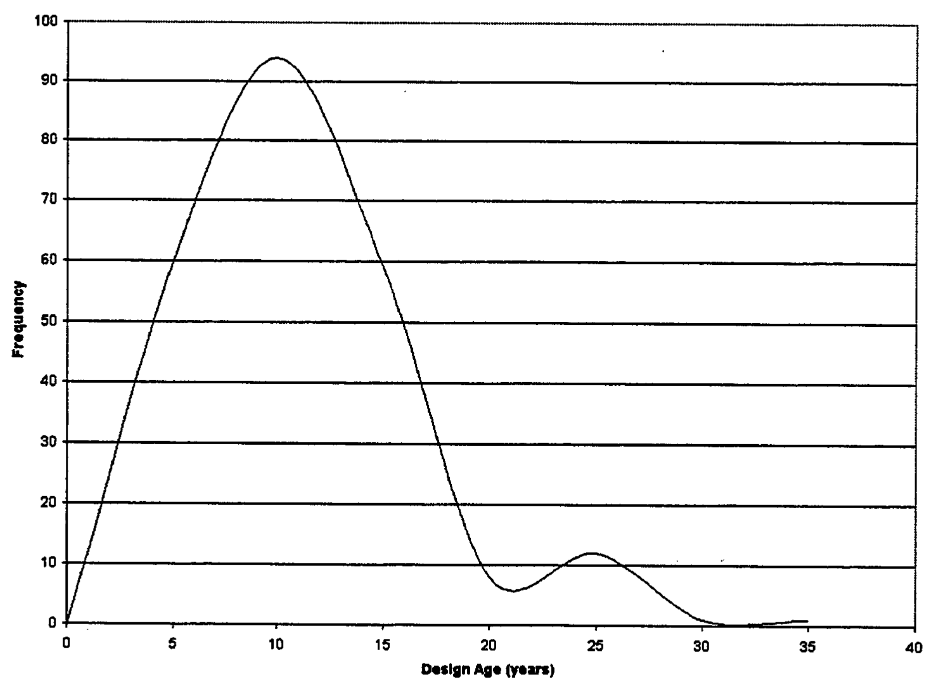


Appendix E: Descriptive Statistics of Design Ages

Design Age (as of 7/10/99)

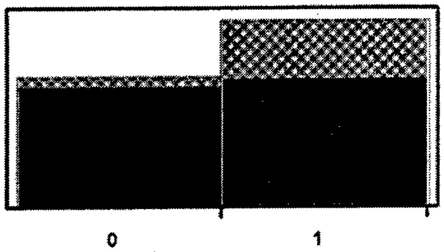
Mean	8.64622559
Standard Error	0.344365424
Median	8.112328767
Mode	7.526027397
Standard Deviation	5.279021993
Sample Variance	27.8680732
Kurtosis	1.952268867
Skewness	1.1157854
Range	30.10410959
Minimum	0.435616438
Maximum	30.53972603
Sum	2031.863014
Count	235

Histogram of Design Age



Appendix F: Distribution of Binary DMSMS Responses

Binary DMSMS



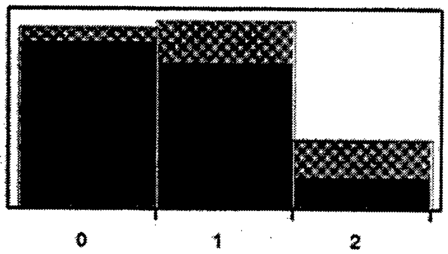
Frequencies

Level	Count	Probability	Cum Prob
0	97	0.41277	0.41277
1	138	0.58723	1.00000
Total	235		

2 Levels

Appendix G: Distribution of Trilevel DMSMS Responses

Trilevel DMSMS



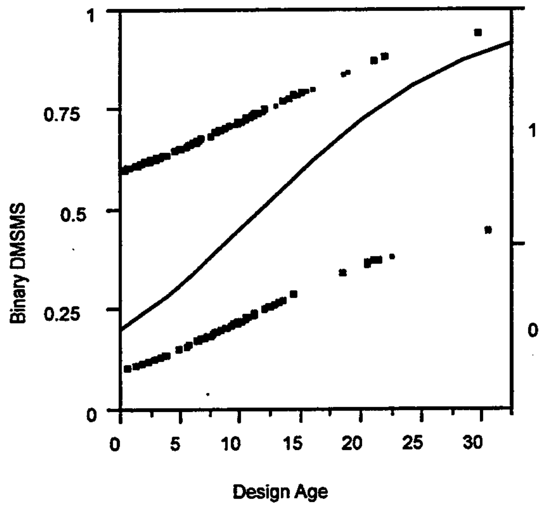
Frequencies

Level	Count	Probability	Cum Prob
0	97	0.41277	0.41277
1	100	0.42553	0.83830
2	38	0.16170	1.00000
Total	235		

3 Levels

Appendix H: Binary DMSMS versus Design Age

Binary DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	9.53641	1	19.07282	<.0001
Full	149.75821			
Reduced	159.29462			

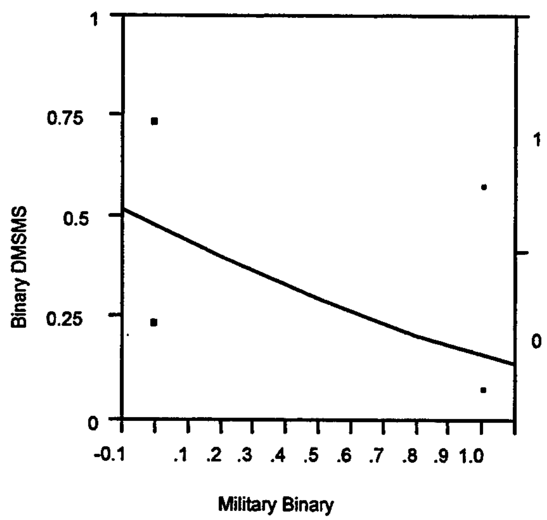
RSquare (U)	0.0599
Observations (or Sum Wgts)	235

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-1.3771747	0.2876382	22.92	<.0001
Design Age	0.11693722	0.0288302	16.45	<.0001

Appendix I: Binary DMSMS versus Military Specificity

Binary DMSMS By Military Binary



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	9.21136	1	18.42273	<.0001
Full	150.08326			
Reduced	159.29462			

RSquare (U)	0.0578
Observations (or Sum Wgts)	235

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.0757118	0.1471483	0.26	0.6069
Military Binary	-1.5825162	0.4128706	14.69	0.0001

Appendix J: Binary DMSMS versus Function

Response: Binary DMSMS

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-162.8895874	Initial	0.09641366	?
2	-156.4973985	Newton	1.03372508	0.04084273
3	-156.240955	Newton	0.08696798	0.00164123
4	-156.1588576	Newton	0.08460971	0.0005257
5	-156.1298572	Newton	0.92175325	0.00018573
6	-156.1193403	Newton	0.91852756	0.00006736
7	-156.1154913	Newton	0.91734986	0.00002465
8	-156.1140781	Newton	0.91691781	0.00000905

Converged by Objective

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	3.18054	11	6.361089	0.8482
Full	156.11408			
Reduced	159.29462			

RSquare (U)	0.0200
Observations (or Sum Wgts)	235

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	-0.9274824	2.9150138	0.10	0.7504
Function[ASIC/Pr-Telecom]	Unstable	0.92748238	2.9555712	0.10	0.7537
Function[Analog-Telecom]	Unstable	0.29149361	2.9392036	0.01	0.9210
Function[Consume-Telecom]	Unstable	0.2343352	3.1220675	0.01	0.9402
Function[Convert-Telecom]	Unstable	0.2343352	2.9856276	0.01	0.9374
Function[Industr-Telecom]	Unstable	1.62062956	3.1220675	0.27	0.6037
Function[Interfa-Telecom]	Unstable	0.74516082	2.9669616	0.06	0.8017
Function[Logic-Telecom]	Unstable	0.61240133	2.9241567	0.04	0.8341
Function[Memory-Telecom]	Unstable	0.6252015	2.9223161	0.05	0.8306
Function[Microco-Telecom]	Unstable	0.2343352	2.9856276	0.01	0.9374
Function[Micropr-Telecom]	Unstable	-7.274979	31.983128	0.05	0.8201
Function[Periphe-Telecom]	Unstable	0.41665675	2.9902759	0.02	0.8892

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Function	11	11	3.0846576	0.9896

Appendix K: Binary DMSMS versus Technology

Response: **Binary DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-162.8895874	Initial	0.77543807	?
2	-155.8593867	Newton	1.13837792	0.04510315
3	-155.602319	Newton	1.04350132	0.00165198
4	-155.5202216	Newton	1.01531656	0.00052786
5	-155.4912212	Newton	1.005549	0.0001865
6	-155.4807042	Newton	1.00203007	0.00006764
7	-155.4768553	Newton	1.00074531	0.00002475
8	-155.475442	Newton	1.00027398	0.00000909

Converged by Objective

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	3.81918	8	7.638361	0.4696
Full	155.47544			
Reduced	159.29462			

RSquare (U)	0.0240
Observations (or Sum Wgts)	235

Parameter Estimates

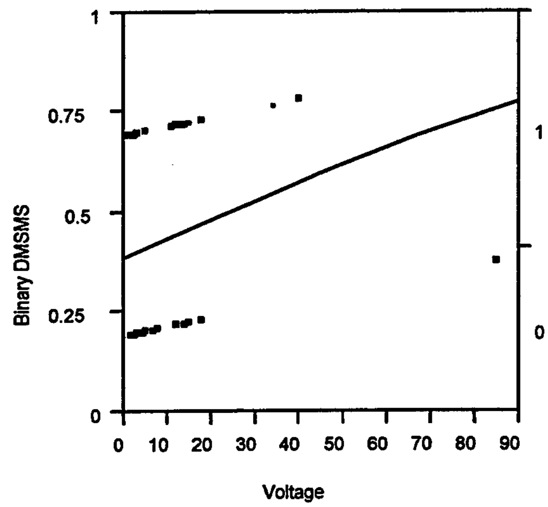
Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept		-0.1118302	8.2254844	0.00	0.9892
Technolo[BICMOS-TTL]		-0.6613597	8.2369929	0.01	0.9360
Technolo[Bipolar-TTL]		-0.4271663	8.2361714	0.00	0.9586
Technolo[CMOS-TTL]		-0.2502845	8.2269423	0.00	0.9757
Technolo[DTL-TTL]	Unstable	8.31429158	53.926278	0.02	0.8775
Technolo[ECL-TTL]	Unstable	-8.0906312	38.572672	0.04	0.8339
Technolo[GAAS-TTL]		0.5172953	8.2647892	0.00	0.9501
Technolo[Hybrid-TTL]		0.11183019	8.2372955	0.00	0.9892
Technolo[MOS-TTL]		0.80497737	8.2608672	0.01	0.9224

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Technology	8	8	3.6286925	0.8890

Appendix L: Binary DMSMS versus Voltage (Continuous)

Binary DMSMS By Voltage



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.41018	1	0.820357	0.3651
Full	158.35061			
Reduced	158.76079			

RSquare (U)	0.0026
Observations (or Sum Wgts)	234

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.4550552	0.1836486	6.14	0.0132
Voltage	0.01883779	0.021966	0.74	0.3911

Appendix M: Binary DMSMS versus Voltage (Nominal)

Response: **Binary DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-162.1964403	Initial	1.60153892	?
2	-146.4498582	Newton	0.9599065	0.10751466
3	-145.0469746	Newton	0.89384017	0.00967126
4	-144.6090618	Newton	0.87026997	0.00302804
5	-144.4543932	Newton	1.14919886	0.00107063
6	-144.3983028	Newton	1.14517722	0.00038842
7	-144.377775	Newton	0.14296362	0.00014217
8	-144.3702376	Newton	0.14289628	0.00005221
9	-144.3674667	Newton	0.14287154	0.00001919
10	-144.3664476	Newton	0.14286244	0.00000706

Converged by Objective

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	14.39434	20	28.78868	0.092
Full	144.36645			
Reduced	158.76079			

RSquare (U)	0.0907
Observations (or Sum Wgts)	234

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	-1.58411	23.682686	0	0.9467
Voltage[1.2-85]	Unstable	-8.61873	158.02781	0	0.9565
Voltage[1.5-85]	Unstable	-8.61873	112.9904	0.01	0.9392
Voltage[1.8-85]	Unstable	1.58411	23.720859	0	0.9468
Voltage[2-85]	Unstable	0.197816	23.706551	0	0.9933
Voltage[2.5-85]	Unstable	1.58411	23.720859	0	0.9468
Voltage[3-85]	Unstable	0.55449	23.68787	0	0.9813
Voltage[3.3-85]	Unstable	0.405455	23.68893	0	0.9863
Voltage[4.5-85]	Unstable	11.78695	158.02781	0.01	0.9405
Voltage[5-85]	Unstable	1.422267	23.683164	0	0.9521
Voltage[5.2-85]	Unstable	-8.61873	93.264013	0.01	0.9264
Voltage[7-85]	Unstable	11.78695	158.02781	0.01	0.9405
Voltage[8-85]	Unstable	11.78695	158.02781	0.01	0.9405
Voltage[11-85]	Unstable	-8.61873	158.02781	0	0.9565
Voltage[12-85]	Unstable	2.682722	23.708141	0.01	0.9099
Voltage[13.2-85]	Unstable	-8.61873	93.264013	0.01	0.9264
Voltage[14-85]	Unstable	1.58411	23.720859	0	0.9468
Voltage[15-85]	Unstable	1.58411	23.720859	0	0.9468

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Voltage[18-85]	Unstable	1.58411	23.70178	0	0.9467
Voltage[34-85]	Unstable	-8.61873	158.02781	0	0.9565
Voltage[40-85]	Unstable	-8.61873	158.02781	0	0.9565

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Voltage	20	20	7.7978208	0.9931

Appendix N: Binary DMSMS versus Military Specificity and Design Age

Response: **Binary DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-162.8895874	Initial	0.12339501	?
2	-136.9815753	Newton	0.49583912	0.18912121
3	-135.8143033	Newton	0.08182133	0.00859398
4	-135.7942131	Newton	0.00192018	0.00014793
5	-135.7942033	Newton	0.00000103	0.00000007

Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	23.50042	2	47.00084	<.0001
Full	135.7942			
Reduced	159.29462			

RSquare (U)	0.1475
Observations (or Sum Wgts)	235

Lack of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack of Fit	143	82.62089	165.2418
Pure Error	89	53.17332	Prob>ChiSq
Total Error	232	135.7942	0.0983

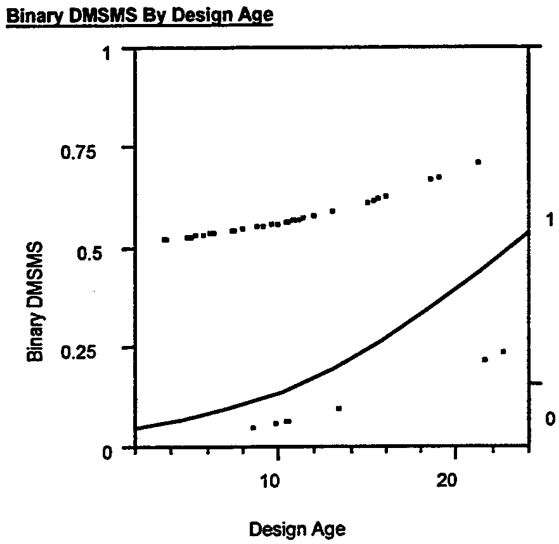
Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-1.3561566	0.3037986	19.93	<.0001
Military Binary	-2.1100827	0.4614352	20.91	<.0001
Design Age	0.15893995	0.0332619	22.83	<.0001

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Military Binary	1	1	20.911128	0
Design Age	1	1	22.83351	0

Appendix O: Binary DMSMS versus Design Age for Military ICs



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	1.685591	1	3.371183	0.0663
Full	20.297903			
Reduced	21.983494			

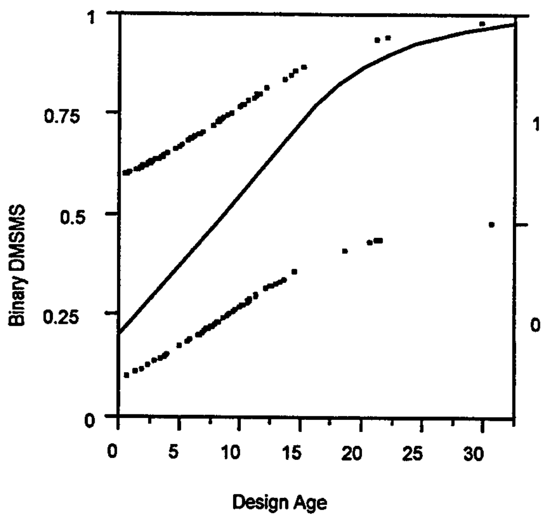
RSquare (U)	0.0767
Observations (or Sum Wgts)	50

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-3.2576782	1.0347496	9.91	0.0016
Design Age	0.14200709	0.0780235	3.31	0.0688

Appendix P: Binary DMSMS versus Non-Military ICs

Binary DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	12.63189	1	25.26379	<.0001
Full	115.46787			
Reduced	128.09976			

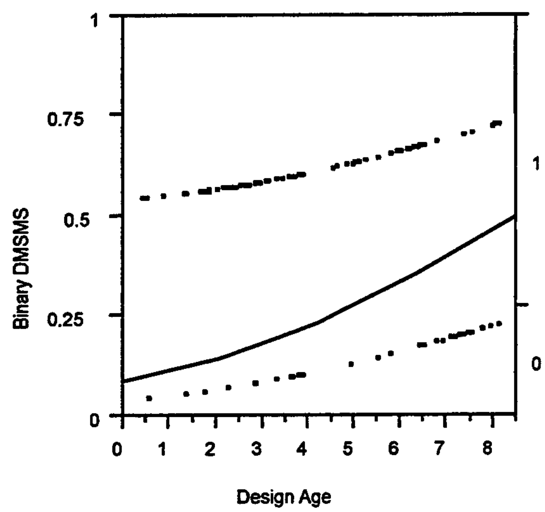
RSquare (U)	0.0986
Observations (or Sum Wgts)	185

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-1.3851273	0.3289787	17.73	<.0001
Design Age	0.16264648	0.0369877	19.34	<.0001

Appendix Q: Binary DMSMS versus Design Age (≤ 8.110 Years)

Binary DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	4.067261	1	8.134521	0.0043
Full	66.189818			
Reduced	70.257079			

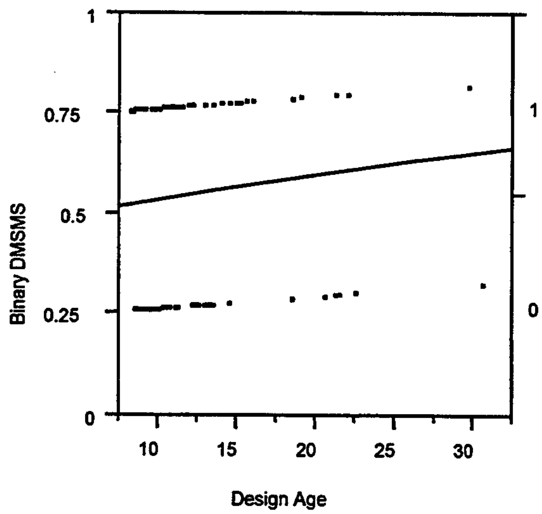
RSquare (U)	0.0579
Observations (or Sum Wgts)	119

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-2.3470709	0.5807314	16.33	<.0001
Design Age	0.27408799	0.1007306	7.40	0.0065

Appendix R: Binary DMSMS versus Design Age (>8.110 Years)

Binary DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.164728	1	0.329457	0.5660
Full	79.618543			
Reduced	79.783271			

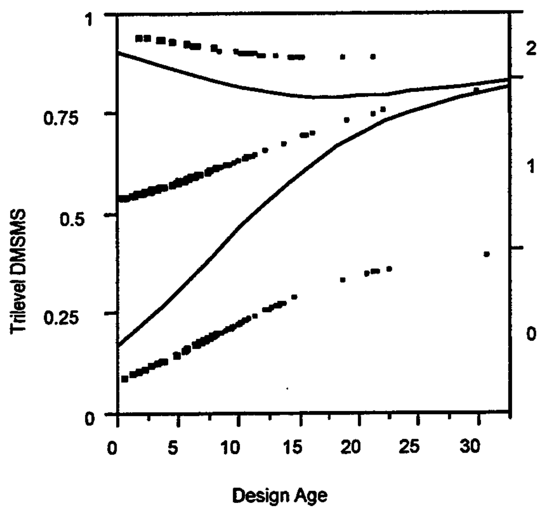
RSquare (U)	0.0021
Observations (or Sum Wgts)	116

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.0999144	0.5697281	0.03	0.8608
Design Age	0.02441036	0.042846	0.32	0.5689

Appendix S: Trilevel DMSMS versus Design Age

Trilevel DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	15.36137	2	30.72273	<.0001
Full	225.14897			
Reduced	240.51034			

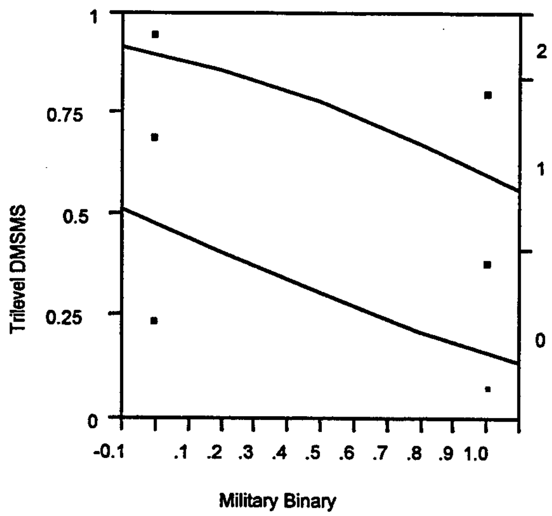
RSquare (U)	0.0639
Observations (or Sum Wgts)	235

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.6463851	0.3976682	2.64	0.1041
Design Age	0.02918876	0.035713	0.67	0.4137
Intercept	2.10243626	0.4049887	26.95	<.0001
Design Age	-0.1432456	0.0424863	11.37	0.0007

Appendix T: Trilevel DMSMS versus Military Specificity

Trilevel DMSMS By Military Binary



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	15.03509	2	30.07018	<.0001
Full	225.47525			
Reduced	240.51034			

RSquare (U)	0.0625
Observations (or Sum Wgts)	235

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	1.59826293	0.2584404	38.25	<.0001
Military Binary	-2.5145537	0.4917229	26.15	<.0001
Intercept	1.46633539	0.261488	31.45	<.0001
Military Binary	-1.3710252	0.4047598	11.47	0.0007

Appendix U: Trilevel DMSMS versus Function

Response: **Trilevel DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-258.1738878	Initial	0.56964104	?
2	-229.4192558	Newton	0.32452128	0.12533115
3	-226.0507726	Newton	0.57511556	0.01490079
4	-225.1993709	Newton	0.58985545	0.00378049
5	-224.9007427	Newton	0.50214712	0.00132776
6	-224.7920947	Newton	0.50078738	0.0004833
7	-224.7522859	Newton	0.5002892	0.00017712
8	-224.7376626	Newton	0.50010633	0.00006507
9	-224.7322859	Newton	0.50003911	0.00002392
10	-224.7303083	Newton	0.50001439	0.0000088

Converged by Objective

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	15.78003	22	31.56006	0.0852
Full	224.73031			
Reduced	240.51034			

RSquare (U)	0.0656
Observations (or Sum Wgts)	235

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	5.127243	24.833303	0.04	0.8364
Function[ASIC/Pr-Telecom]	Unstable	-4.27994	24.841291	0.03	0.8632
Function[Analog-Telecom]	Unstable	-4.53946	24.838522	0.03	0.855
Function[Consume-Telecom]	Unstable	4.2508	102.33611	0	0.9669
Function[Convert-Telecom]	Unstable	4.2508	62.466165	0	0.9457
Function[Industr-Telecom]	Unstable	4.943948	102.33407	0	0.9615
Function[Interfa-Telecom]	Unstable	-4.21095	24.845045	0.03	0.8654
Function[Logic-Telecom]	Unstable	-4.72178	24.834856	0.04	0.8492
Function[Memory-Telecom]	Unstable	-3.90347	24.835474	0.02	0.8751
Function[Microco-Telecom]	Unstable	4.2508	62.466165	0	0.9457
Function[Micropr-Telecom]	Unstable	-5.12724	198.27569	0	0.9794
Function[Periphe-Telecom]	Unstable	4.319915	64.320315	0	0.9465
Intercept	Unstable	6.115043	21.341473	0.08	0.7745
Function[ASIC/Pr-Telecom]	Unstable	-5.82736	21.352859	0.07	0.7849
Function[Analog-Telecom]	Unstable	-5.23957	21.347004	0.06	0.8061
Function[Consume-Telecom]	Unstable	3.956147	101.54323	0	0.9689
Function[Convert-Telecom]	Unstable	3.956147	61.160841	0	0.9484
Function[Industr-Telecom]	Unstable	3.263	101.54529	0	0.9744

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Function[Interfa-Telecom]	Unstable	-5.4219	21.356111	0.06	0.7996
Function[Logic-Telecom]	Unstable	-6.06098	21.343586	0.08	0.7764
Function[Memory-Telecom]	Unstable	-4.83411	21.343968	0.05	0.8208
Function[Microco-Telecom]	Unstable	3.956147	61.160841	0	0.9484
Function[Micropr-Telecom]	Unstable	5.036221	140.72674	0	0.9715
Function[Periphe-Telecom]	Unstable	3.842941	63.053607	0	0.9514

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Function	22	22	11.319143	0.9699

Appendix V: Trilevel DMSMS versus Technology

Response: **Trilevel DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-258.1738878	Initial	0.0443524	?
2	-230.6880097	Newton	0.74871784	0.11914224
3	-227.727486	Newton	0.51846898	0.01299972
4	-227.0322169	Newton	0.56028049	0.00306229
5	-226.7949917	Newton	0.44626755	0.00104594
6	-226.7088045	Newton	0.44516701	0.00038015
7	-226.6772329	Newton	0.44470983	0.00013927
8	-226.6656364	Newton	0.44454202	0.00005116
9	-226.6613728	Newton	0.44448033	0.00001881
10	-226.6598046	Newton	0.44445765	0.00000692

Converged by Objective

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	13.85053	16	27.70107	0.0343
Full	226.6598			
Reduced	240.51034			

RSquare (U)	0.0576
Observations (or Sum Wgts)	235

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	4.89367507	43.575363	0.01	0.9106
Technolo[BICMOS-TTL]	Unstable	-3.1019156	43.585774	0.01	0.9433
Technolo[Bipolar-TTL]	Unstable	-4.5572028	43.578423	0.01	0.9167
Technolo[CMOS-TTL]	Unstable	-3.9308643	43.57595	0.01	0.9281
Technolo[DTL-TTL]	Unstable	6.25758881	236.80112	0	0.9789
Technolo[ECL-TTL]	Unstable	-4.8936751	236.79948	0	0.9835
Technolo[GAAS-TTL]	Unstable	5.00014377	83.872044	0	0.9525
Technolo[Hybrid-TTL]	Unstable	4.77503097	58.621797	0.01	0.9351
Technolo[MOS-TTL]	Unstable	5.17751524	80.610658	0	0.9488
Intercept	Unstable	4.81366617	48.257355	0.01	0.9205
Technolo[BICMOS-TTL]	Unstable	-2.3287595	48.266085	0	0.9615
Technolo[Bipolar-TTL]	Unstable	-4.4771939	48.260118	0.01	0.9261
Technolo[CMOS-TTL]	Unstable	-3.7977456	48.257878	0.01	0.9373
Technolo[DTL-TTL]	Unstable	-4.8136662	332.68474	0	0.9885
Technolo[ECL-TTL]	Unstable	6.33759771	171.51312	0	0.9705
Technolo[GAAS-TTL]	Unstable	4.67468756	86.397972	0	0.9569
Technolo[Hybrid-TTL]	Unstable	4.85503987	62.180987	0.01	0.9378
Technolo[MOS-TTL]	Unstable	4.56437696	83.236006	0	0.9563

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Technology	16	16	11.26332	0.7929

Appendix W: Trilevel DMSMS versus Voltage (Continuous)

Response: **Trilevel DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-257.0752755	Initial	0.01269865	?
2	-239.676301	Newton	0.17312274	0.07259061
3	-239.1579571	Newton	0.00022271	0.00216728
4	-239.1564662	Newton	0.0000007	0.00000623

Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.49657	2	0.993141	0.6086
Full	239.15647			
Reduced	239.65304			

RSquare (U)	0.0021
Observations (or Sum Wgts)	234

Lack of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack of Fit	38	22.74179	45.48357
Pure Error	192	216.41468	Prob>ChiSq
Total Error	230	239.15647	0.1886

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.88023275	0.255768	11.84	0.0006
Voltage	0.0094443	0.0287978	0.11	0.7429
Intercept	1.04012888	0.273723	14.44	0.0001
Voltage	-0.0148399	0.034918	0.18	0.6708

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Voltage	2	2	0.81881386	0.664

Appendix X: Trilevel DMSMS versus Voltage (Nominal)

Response: **Trilevel DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-257.0752755	Initial	2.09548465	?
2	-220.1766349	Newton	0.72024678	0.16757893
3	-217.4928792	Newton	0.61556699	0.01233894
4	-216.7998782	Newton	0.67330617	0.00319635
5	-216.5552097	Newton	0.33479865	0.00112977
6	-216.4662209	Newton	0.33386983	0.00041108
7	-216.433619	Newton	0.33353038	0.00015063
8	-216.4216437	Newton	0.28577681	0.00005533
9	-216.4172406	Newton	0.28573728	0.00002034
10	-216.4156212	Newton	0.28572275	0.00000748

Converged by Objective

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	23.23742	40	46.47483	0.2231
Full	216.41562			
Reduced	239.65304			

RSquare (U)	0.097
Observations (or Sum Wgts)	234

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	3.10881896	45.318265	0	0.9453
Voltage[1.2-85]	Unstable	-3.108819	357.90217	0	0.9931
Voltage[1.5-85]	Unstable	-12.777525	127.92105	0.01	0.9204
Voltage[1.8-85]	Unstable	6.55988708	127.92105	0	0.9591
Voltage[2-85]	Unstable	-3.8019661	45.333236	0.01	0.9332
Voltage[2.5-85]	Unstable	6.55988708	127.92105	0	0.9591
Voltage[3-85]	Unstable	-2.1925282	45.325253	0	0.9614
Voltage[3.3-85]	Unstable	-2.4156718	45.325752	0	0.9575
Voltage[4.5-85]	Unstable	8.04244492	255.09755	0	0.9748
Voltage[5-85]	Unstable	-2.1369584	45.318757	0	0.9624
Voltage[5.2-85]	Unstable	-3.108819	209.92177	0	0.9882
Voltage[7-85]	Unstable	8.04244492	255.09755	0	0.9748
Voltage[8-85]	Unstable	8.04244492	255.09755	0	0.9748
Voltage[11-85]	Unstable	-3.108819	357.90217	0	0.9931
Voltage[12-85]	Unstable	7.20636124	105.63339	0	0.9456
Voltage[13.2-85]	Unstable	-12.486862	112.93596	0.01	0.912
Voltage[14-85]	Unstable	6.55988708	127.92105	0	0.9591
Voltage[15-85]	Unstable	-3.108819	45.338226	0	0.9453

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Voltage[18-85]	Unstable	6.55988708	95.96234	0	0.9455
Voltage[34-85]	Unstable	-14.260083	255.09755	0	0.9554
Voltage[40-85]	Unstable	-3.108819	357.90217	0	0.9931
Intercept	Unstable	3.64816502	46.176017	0.01	0.937
Voltage[1.2-85]	Unstable	7.50309886	255.25132	0	0.9765
Voltage[1.5-85]	Unstable	-3.648165	46.195608	0.01	0.9371
Voltage[1.8-85]	Unstable	6.02054102	128.22744	0	0.9626
Voltage[2-85]	Unstable	-3.648165	46.185813	0.01	0.937
Voltage[2.5-85]	Unstable	6.02054102	128.22744	0	0.9626
Voltage[3-85]	Unstable	-1.8564055	46.181732	0	0.9679
Voltage[3.3-85]	Unstable	-1.9434169	46.181806	0	0.9664
Voltage[4.5-85]	Unstable	-3.648165	358.01179	0	0.9919
Voltage[5-85]	Unstable	-2.9028321	46.176533	0	0.9499
Voltage[5.2-85]	Unstable	7.50309886	152.11584	0	0.9607
Voltage[7-85]	Unstable	-3.648165	358.01179	0	0.9919
Voltage[8-85]	Unstable	-3.648165	358.01179	0	0.9919
Voltage[11-85]	Unstable	7.50309886	255.25132	0	0.9765
Voltage[12-85]	Unstable	5.5684029	106.00705	0	0.9581
Voltage[13.2-85]	Unstable	-2.9550178	46.190711	0	0.949
Voltage[14-85]	Unstable	6.02054102	128.22744	0	0.9626
Voltage[15-85]	Unstable	-13.316871	128.22744	0.01	0.9173
Voltage[18-85]	Unstable	6.02054102	96.370379	0	0.9502
Voltage[34-85]	Unstable	-14.799429	255.25132	0	0.9538
Voltage[40-85]	Unstable	7.50309886	255.25132	0	0.9765

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Voltage	40	40	12.239432	1

Appendix Y: Trilevel DMSMS versus Design Age and Military Specificity

Response: **Trilevel DMSMS**

Iteration History

Iter	LogLikelihood	Step	Delta-Criterion	Obj-Criterion
1	-258.1738878	Initial	0.10183962	?
2	-209.5916621	Newton	0.35852419	0.23178359
3	-207.9739887	Newton	0.05558694	0.00777787
4	-207.9530386	Newton	0.00115491	0.00010074
5	-207.9530313	Newton	0.00000045	0.00000004

Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	32.55731	4	65.11461	<.0001
Full	207.95303			
Reduced	240.51034			

RSquare (U)	0.1354
Observations (or Sum Wgts)	235

Lack of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack of Fit	286	140.07163	280.1433
Pure Error	-57	67.8814	Prob>ChiSq
Total Error	229	207.95303	0.5865

Parameter Estimates

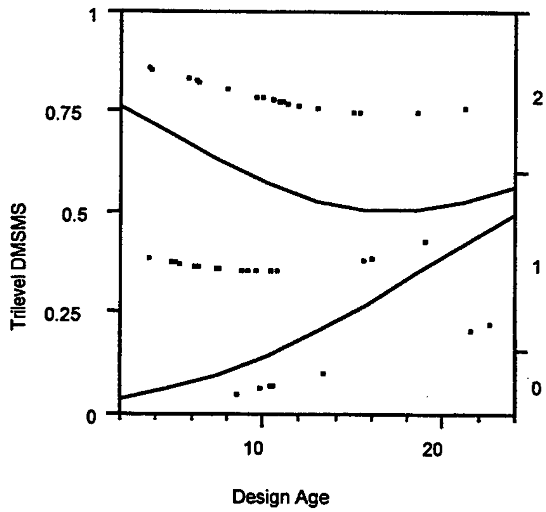
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.89473709	0.4514581	3.93	0.0475
Military Binary	-2.7268879	0.5207138	27.42	<.0001
Design Age	0.07764847	0.0437907	3.14	0.0762
Intercept	2.29056877	0.4372159	27.45	<.0001
Military Binary	-1.0500933	0.4258485	6.08	0.0137
Design Age	-0.118243	0.0465467	6.45	0.0111

Effect Test

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
Military Binary	2	2	27.43589	0
Design Age	2	2	26.55023	0

Appendix Z: Trilevel DMSMS versus Design Age for Military ICs

Trilevel DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	3.285243	2	6.570485	0.0374
Full	47.762796			
Reduced	51.048038			

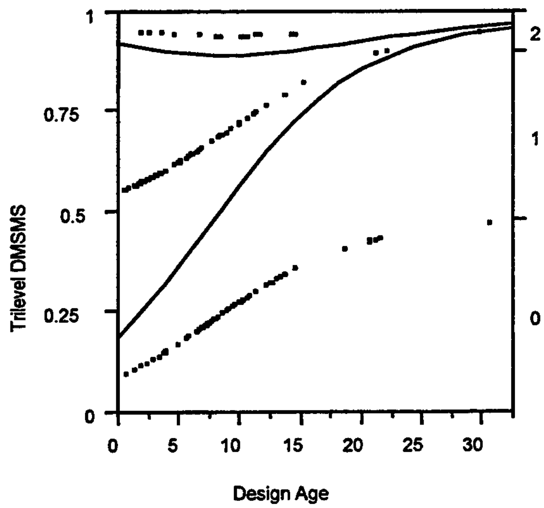
RSquare (U)	0.0644
Observations (or Sum Wgts)	50

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-1.964745	1.1107304	3.13	0.0769
Design Age	0.08761222	0.0829301	1.12	0.2908
Intercept	1.39631705	0.8245149	2.87	0.0904
Design Age	-0.135354	0.0801536	2.85	0.0913

Appendix AA: Trilevel DMSMS versus Design Age for Non-Military ICs

Trilevel DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	14.28895	2	28.57789	<.0001
Full	160.13827			
Reduced	174.42721			

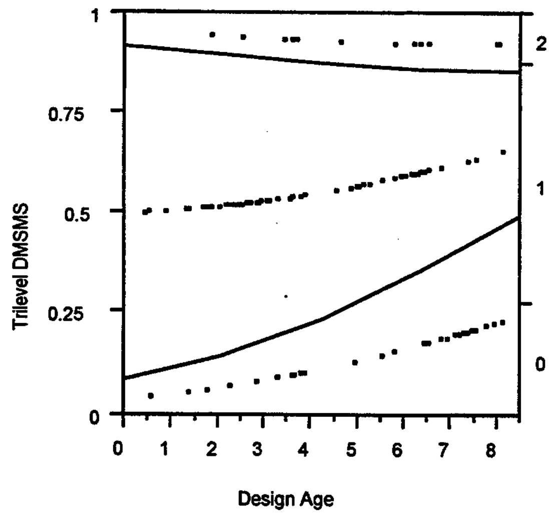
RSquare (U)	0.0819
Observations (or Sum Wgts)	185

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.88723935	0.5237816	2.87	0.0903
Design Age	0.07887682	0.0547071	2.08	0.1494
Intercept	2.2438249	0.5212207	18.53	<.0001
Design Age	-0.1115481	0.0597823	3.48	0.0621

Appendix BB: Trilevel DMSMS versus Design Age (≤8.110 Years)

Trilevel DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	4.89989	2	9.799774	0.0074
Full	105.16003			
Reduced	110.05992			

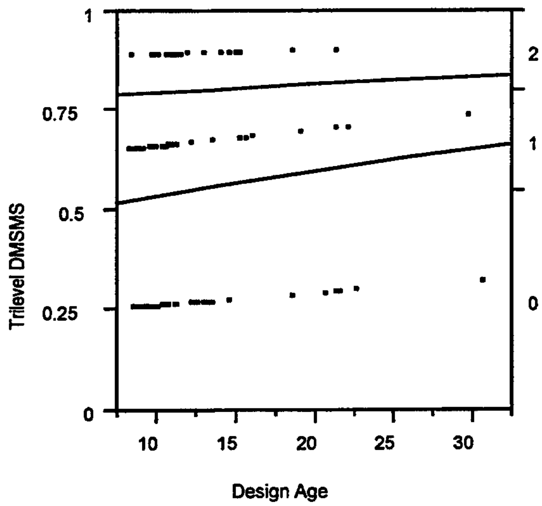
RSquare (U)	0.0445
Observations (or Sum Wgts)	119

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	0.04477703	0.8372425	0.00	0.9573
Design Age		0.13789763	0.1466773	0.88	0.3471
Intercept		2.33247869	0.7057078	10.92	0.0009
Design Age		-0.1664968	0.1306295	1.62	0.2025

Appendix CC: Trilevel DMSMS versus Design Age (>8.110 Years)

Trilevel DMSMS By Design Age



Converged by Gradient

Whole-Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.16989	2	0.339788	0.8438
Full	115.31010			
Reduced	115.48000			

RSquare (U)	0.0015
Observations (or Sum Wgts)	116

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.76193657	0.7431259	1.05	0.3052
Design Age	0.02069344	0.0560289	0.14	0.7119
Intercept	0.31530067	0.8674459	0.13	0.7162
Design Age	-0.0067465	0.0663265	0.01	0.9190

Appendix DD: Data

Function	Part #	Technology	Voltage	Military	Data-sheet Date	Design Age (as of 7/10/99)	Generic flag	DMSMS	DMSMS Trilevel
ASIC	Q6200J	CMOS	5	No	08/01/86	12.95	Red	0	0
ASIC	PLS159A	TTL	5	No	01/01/92	7.53	Yellow	1	1
ASIC	VGT200180	CMOS	5	No	05/11/88	11.17	Red	0	0
ASIC	XC8100-1PC44C	CMOS	3.3	No	10/01/95	3.78	Red	0	0
ASIC	M38510/50612BRX	TTL	5	Yes	08/30/84	14.87	Green	1	2
ASIC	5962-85155142A	TTL	5	Yes	07/21/88	10.98	Green	1	2
ASIC	MSM10V0416PGA88C	CMOS	5	No	11/01/88	10.69	Red	0	0
ASIC	GAL26CV12-15LJ	CMOS	5	No	01/01/92	7.53	Yellow	1	1
ASIC	5962-8984112KA	CMOS	5	Yes	11/28/89	9.62	Green	1	2
ASIC	CY331-25WC	CMOS	5	No	08/01/93	5.94	Yellow	1	1
Consumer	AN5531	Bipolar	12	No	01/01/87	12.53	Red	0	0
Consumer	U4930B-A	Bipolar	5	No	01/28/97	2.45	Yellow	1	1
Consumer	M52301SP	Bipolar	5	No	09/01/95	3.86	Yellow	1	1
Microprocessor	Z8S18033PEC	CMOS	5	No	01/01/89	10.53	Yellow	1	1
Microprocessor	BX80525U500512E	BICMOS	1.5	No	02/01/99	0.44	Yellow	1	1
Microprocessor	8000301UX	MOS	5	Yes	07/21/80	18.98	Yellow	1	1
Memory	MN6311S	MOS	3	No	10/10/97	1.75	Yellow	1	1
Memory	CY7C4282-25ASC	CMOS	5	No	09/05/97	1.84	Yellow	1	1
Memory	M38510/05701SXB	CMOS	5	Yes	04/30/84	15.20	Green	1	2
Memory	PUMA77F16006MB15	CMOS	5	No	09/01/95	3.86	Yellow	1	1
Memory	MS6398-70FC	CMOS	5	No	06/01/91	8.11	Red	0	0
Memory	MT53C4K18D4EJ25	CMOS	5	No	01/01/93	6.52	Red	0	0
Memory	HN29VB800T12	CMOS	3	No	06/14/96	3.07	Yellow	1	1
Memory	KM48S2021BT-G9	CMOS	3.3	No	12/01/96	2.61	Yellow	1	1
Memory	MCM6223TS12	CMOS	5	No	09/01/96	2.85	Red	0	0
Memory	HM1-6562-9	CMOS	5	No	01/01/81	18.53	Red	0	0
Logic	74S182DCQM	TTL	5	No	06/01/89	10.11	Green	1	2
Logic	74AC11841N	CMOS	3.3	No	01/01/90	9.53	Red	0	0
Logic	P54FCT3843DDM	CMOS	3.3	No	01/01/92	7.53	Red	0	0
Logic	54ABT646CLM	BICMOS	5	No	01/01/93	6.52	Green	1	2
Logic	54AHCT148J	CMOS	5	No	01/01/94	5.52	Red	0	0
Logic	SG51-02	TTL	5	No	01/01/90	9.53	Red	0	0
Logic	54HC4020/BEAJC	CMOS	2	Yes	03/01/89	10.36	Yellow	1	1
Logic	SNJ54LVTH18652AHV	BICMOS	3.3	Yes	07/01/94	5.03	Yellow	1	1
Logic	CD54HC21F	CMOS	2	No	08/01/89	9.95	Green	1	2
Logic	14GC10	Hybrid	5	No	01/01/91	8.53	Red	0	0
Tele/Datacomm	AM79C410XKC	CMOS	3	No	02/01/93	6.44	Red	0	0
Tele/Datacomm	AK2356	CMOS	3	No	08/01/91	7.95	Red	0	0
Tele/Datacomm	PSB2113F	CMOS	5	No	07/01/97	2.02	Yellow	1	1
Tele/Datacomm	AM79M574JC	CMOS	5	No	08/09/89	9.92	Yellow	1	1
Tele/Datacomm	W91462	CMOS	2	No	01/01/92	7.53	Red	0	0
Analog	MAX757C/D	CMOS	5	No	10/01/93	5.78	Yellow	1	1
Analog	LM4250H	Bipolar	1.5	No	01/01/93	6.52	Green	1	2
Analog	LM2419T	Bipolar	85	No	10/01/92	6.78	Red	0	0

Function	Part #	Technology	Voltage	Military	Data-sheet Date	Design Age (as of 7/10/99)	Generic flag	DMSMS	DMSMS Trilevel
Analog	AT233PIN	GAAS	5	No	09/01/96	2.85	Yellow	1	1
Analog	SA9502DH	BICMOS	3	No	12/10/98	0.58	Red	0	0
Analog	TDA7370V	Bipolar	18	No	06/01/91	8.11	Yellow	1	1
Analog	TSC9420EPA	CMOS	2.5	No	05/01/88	11.20	Red	0	0
Analog	LTC1753CG	BICMOS	13.2	No	09/01/98	0.85	Yellow	1	1
Analog	TA8233AH	Bipolar	13.2	No	08/28/97	1.87	Green	1	2
Analog	LMC662AIMX	CMOS	5	No	01/01/93	6.52	Yellow	1	1
Microcontroller	AT89LS53-12JI	CMOS	3	No	01/01/97	2.52	Yellow	1	1
Microcontroller	SM8505(QFP)	CMOS	1.8	No	04/01/96	3.27	Red	0	0
Microcontroller	MB8851H-PSH	CMOS	5	No	06/01/87	12.12	Red	0	0
Microcontroller	P83C750EBP	CMOS	5	No	03/01/93	6.36	Yellow	1	1
Microcontroller	TMP47C416F	CMOS	3	No	01/01/97	2.52	Yellow	1	1
Microcontroller	SM8314(QFP)	CMOS	3	No	03/01/97	2.36	Yellow	1	1
Microcontroller	HD404614TF	CMOS	3	No	06/01/91	8.11	Yellow	1	1
Microcontroller	MB88507PSH	CMOS	5	No	06/01/87	12.12	Red	0	0
Microcontroller	TMP47C103N	CMOS	2	No	01/01/97	2.52	Yellow	1	1
Analog	5962-8715602CX	Bipolar	5	Yes	09/22/93	5.80	Green	1	2
Analog	LTC1144CS8	CMOS	18	No	06/01/94	5.11	Yellow	1	1
Analog	TQ9141D	GAAS	8	No	08/19/92	6.89	Red	0	0
Analog	5962-9083802HXX	Bipolar	34	Yes	03/10/93	6.34	Green	1	2
Analog	78SR110VC	Hybrid	5	No	07/01/94	5.03	Yellow	1	1
Analog	MSP3410B(PLCC68)	CMOS	5	No	11/20/95	3.64	Red	0	0
Analog	DA0956	TTL	5	No	01/01/93	6.52	Yellow	1	1
Analog	ADA25102FIC	GAAS	5	No	01/01/90	9.53	Red	0	0
Analog	UPC29M08HF	Bipolar	11	No	07/01/97	2.02	Yellow	1	1
Analog	AN79N20	Bipolar	40	No	04/01/88	11.28	Yellow	1	1
Analog	M38510/11903SDA	Bipolar	15	Yes	08/07/87	11.93	Green	1	2
Analog	TDA9206	Bipolar	12	No	10/01/95	3.78	Yellow	1	1
Analog	LM1812N/B+	Bipolar	18	No	01/01/89	10.53	Red	0	0
Analog	AM0210A	GAAS	5	No	10/03/88	10.77	Red	0	0
Analog	UCC3883D	BICMOS	18	No	04/01/90	9.28	Red	0	0
Analog	TA8208	Bipolar	13.2	No	08/28/97	1.87	Yellow	1	1
ASIC	MBCC2700XXX9	CMOS	5	No	05/01/86	13.20	Red	0	0
ASIC	M38510/60601BUX	CMOS	5	No	04/21/88	11.22	Yellow	1	1
ASIC	SLA5040DIE	CMOS	5	No	01/01/86	13.53	Red	0	0
ASIC	VGT100528DIE	CMOS	5	No	02/01/87	12.44	Red	0	0
Logic	5962-9457401QXX	BICMOS	5	Yes	09/07/94	4.84	Yellow	1	1
Logic	SN54BCT374FK	BICMOS	5	No	10/01/89	9.78	Yellow	1	1
Logic	9D20	Hybrid	5	Yes	01/01/91	8.53	Red	0	0
Logic	SN74S20D	TTL	5	No	01/01/85	14.53	Green	1	2
Logic	KS74HCTLSJ	CMOS	5	No	08/01/89	9.95	Red	0	0
Logic	PI3C3861S	CMOS	5	No	01/01/93	6.52	Green	1	2
Logic	FM5402FMQB	TTL	5	Yes	01/01/89	10.53	Green	1	2
Logic	V74ACT822DS	CMOS	5	No	06/01/89	10.11	Red	0	0

Function	Part #	Technology	Voltage	Military	Data-sheet Date	Design Age (as of 7/10/99)	Generic flag	DMSMS	DMSMS Trilevel
Logic	SN74CBT16213DL	CMOS	5	No	08/01/96	2.94	Yellow	1	1
Logic	M38510H05203BTX	CMOS	5	Yes	04/30/84	15.20	Green	1	2
Logic	5962-8975701LX	TTL	5	Yes	09/24/90	8.80	Yellow	1	1
Logic	MC14548BCPD	CMOS	5	No	01/01/85	14.53	Red	0	0
Logic	IDT54FCT162240ATEB	CMOS	5	Yes	01/01/92	7.53	Yellow	1	1
Logic	54ACTQ240DMQB	CMOS	5	Yes	01/01/90	9.53	Yellow	1	1
Logic	CDC204-7N	CMOS	5	No	06/01/94	5.11	Yellow	1	1
Logic	CD54ACT654F	CMOS	5	No	04/01/88	11.28	Red	0	0
Logic	N82S33FB	TTL	5	No	05/01/78	21.21	Red	0	0
Logic	PECLDL10-10	Hybrid	5.2	No	01/01/92	7.53	Yellow	1	1
Logic	SN54S268J	TTL	5	No	01/01/85	14.53	Red	0	0
Logic	54HCTL3273J	CMOS	5	No	01/01/92	7.53	Red	0	0
Logic	NC7S08M5	CMOS	2	No	02/01/96	3.44	Green	1	2
Logic	S5412W/833B	TTL	5	Yes	05/01/78	21.21	Green	1	2
Logic	14FTD250	Hybrid	5	No	01/01/91	8.53	Red	0	0
Logic	SMD99C5060	Hybrid	5	No	05/01/91	8.20	Yellow	1	1
Logic	74F350PC	TTL	5	No	07/01/85	14.03	Green	1	2
Logic	U6A910959X	DTL	12	No	01/01/69	30.54	Red	0	0
Logic	5962R9574101VXC	CMOS	5	Yes	11/01/95	3.69	Green	1	2
Logic	74LVT20PW	BICMOS	3.3	No	8/28/96	2.87	Yellow	1	1
Logic	IDT54FCT540540D	CMOS	5	No	01/01/88	11.53	Green	1	2
Logic	MC74BC374P	BICMOS	5	No	03/01/90	9.36	Red	0	0
Logic	8TD200	Hybrid	5	No	01/01/91	8.53	Yellow	1	1
Logic	SN74S310N	TTL	7	No	01/01/86	13.53	Red	0	0
Logic	MM74C93J	CMOS	3	No	01/01/88	11.53	Green	1	2
Logic	HD74AC4511P	CMOS	3.3	No	09/01/89	9.86	Red	0	0
Logic	DM75L12W/883	TTL	5	Yes	01/01/81	18.53	Green	1	2
Logic	SN74LVC16245ADL	CMOS	3.3	No	12/01/94	4.61	Green	1	2
Logic	ZX74HCTLS393J	CMOS	5	No	01/01/85	14.53	Red	0	0
Logic	MC1208L	ECL	14	No	12/01/69	29.62	Yellow	1	1
Logic	10117F-B	ECL	5.2	No	01/01/86	13.53	Yellow	1	1
Logic	SNJ54LVT162374WD	BICMOS	3.3	Yes	03/01/92	7.36	Yellow	1	1
Logic	SMT28CA101	Hybrid	5	No	06/01/91	8.11	Red	0	0
Logic	DM8123N/B+	TTL	5	No	01/01/89	10.53	Red	0	0
Logic	VB74ACT826DS	CMOS	5	No	06/01/89	10.11	Red	0	0
Logic	14TDL35	Hybrid	5	No	01/01/91	8.53	Red	0	0
Logic	M38510/33201BSB	TTL	5	Yes	08/09/83	15.93	Yellow	1	1
Logic	IDT74ALVCH245PG	CMOS	3.3	No	01/01/99	0.52	Yellow	1	1
Logic	TC40H366P	CMOS	5	No	01/01/85	14.53	Red	0	0
Logic	9H40FM	TTL	5	No	12/01/78	20.62	Red	0	0
Logic	SN74F153	TTL	5	No	01/01/89	10.53	Green	1	2
Logic	14LG400	Hybrid	5	No	01/01/91	8.53	Red	0	0
Logic	5962R9665602VEC	CMOS	3	Yes	12/12/95	3.58	Green	1	2

Function	Part #	Technology	Voltage	Military	Data-sheet Date	Design Age (as of 7/10/99)	Generic flag	DMSMS	DMSMS Trilevel
Logic	74LVT126D-T	BICMOS	3.3	No	12/21/95	3.55	Yellow	1	1
Logic	M38510/15201BLB	TTL	5	Yes	07/21/86	12.98	Green	1	2
Logic	TIM9908N	TTL	5	No	04/01/88	11.28	Red	0	0
Memory	CY100E470-7DC	BICMOS	4.5	No	03/01/92	7.36	Red	0	0
Memory	QS723611-20TF	CMOS	5	No	06/01/96	3.11	Yellow	1	1
Memory	HM6789HAJP20	BICMOS	5	No	03/01/91	8.36	Yellow	1	1
Memory	MCM62983J12	CMOS	5	No	07/01/90	9.03	Red	0	0
Memory	EDI8F44128C25MMC	CMOS	5	No	01/01/93	6.52	Red	0	0
Memory	TC8890F-XXXX	CMOS	5	No	03/01/91	8.36	Yellow	1	1
Memory	TMS4000NC	MOS	12	No	01/01/91	8.53	Red	0	0
Memory	5962-9062012MXX	CMOS	5	Yes	03/11/93	6.33	Yellow	1	1
Memory	AM27S41LM	TTL	5	Yes	01/01/84	15.53	Yellow	1	1
Memory	2613-20F	MOS	5	No	01/01/79	20.53	Red	0	0
Memory	5962-8976405MZA	CMOS	5	Yes	05/04/93	6.19	Yellow	1	1
Memory	X25057V1.8	CMOS	1.8	No	05/08/97	2.17	Yellow	1	1
Memory	MC22005F1DB1B10	Hybrid	3	No	03/01/98	1.36	Red	0	0
Memory	KM332F104RT-L6	CMOS	3.3	No	04/01/96	3.27	Yellow	1	1
Memory	HMS188CSBSLP15	CMOS	5	Yes	10/01/89	9.78	Red	0	0
Memory	MCM7649PCD	TTL	5	No	05/01/84	15.20	Yellow	1	1
Memory	5962-3829406MUA	CMOS	5	Yes	04/04/88	11.27	Green	1	2
Memory	L7C171KME25	CMOS	5	Yes	03/01/89	10.36	Red	0	0
Memory	W23C8192-15	CMOS	5	No	02/01/92	7.44	Red	0	0
Memory	M38510/20909BKX	TTL	5	Yes	10/11/88	10.75	Yellow	1	1
Memory	STK22C48S45	CMOS	5	No	03/01/97	2.36	Yellow	1	1
Memory	L8C201MMB20	CMOS	5	Yes	12/11/95	3.58	Yellow	1	1
Memory	CYM1641HD45C	CMOS	5	No	02/01/89	10.44	Red	0	0
Memory	5962-9220504MLA	CMOS	5	Yes	04/28/93	6.20	Green	1	2
Memory	TC524257Z12	CMOS	5	No	02/01/89	10.44	Red	0	0
Memory	KM48C81004AK6	CMOS	5	No	12/01/95	3.61	Red	0	0
Memory	MT2D88C25632-8	CMOS	5	No	08/01/94	4.94	Red	0	0
Memory	D8101A4	MOS	5	No	01/01/79	20.53	Red	0	0
Memory	HB56U432B6BN	CMOS	5	No	02/07/97	2.42	Yellow	1	1
Memory	5962-8684604VX	CMOS	5	Yes	01/27/89	10.45	Yellow	1	1
Memory	TC57H256	CMOS	5	No	01/01/92	7.53	Yellow	1	1
Memory	CXK5416P35	CMOS	5	No	01/01/87	12.53	Red	0	0
Memory	63S1641ANSHRP	TTL	5	No	01/01/78	21.53	Red	0	0
Memory	MAT6216FS2	CMOS	5	Yes	06/01/88	11.11	Green	1	2
Memory	HM9-7641AR2	TTL	5	No	01/01/78	21.53	Red	0	0
Memory	5962-8751401YX	CMOS	5	Yes	08/07/89	9.93	Green	1	2
Memory	AM99C165-55DCB	CMOS	5	No	06/01/87	12.12	Yellow	1	1
Memory	5962-3826705MZA	CMOS	5	Yes	07/12/91	8.00	Green	1	2
Memory	MT4C4003JCNIT	CMOS	5	No	04/01/92	7.28	Red	0	0
Memory	DM86L90N/A+	TTL	5	No	01/01/87	12.53	Red	0	0

Function	Part #	Technology	Voltage	Military	Data-sheet Date	Design Age (as of 7/10/99)	Generic flag	DMSMS	DMSMS Trilevel
Memory	MCM516180AJ70R	CMOS	5	No	10/01/93	5.78	Red	0	0
Memory	MH16V6445BWJ5	CMOS	3.3	No	02/26/97	2.37	Yellow	1	1
Memory	74LS295ANA+1	TTL	5	No	07/01/77	22.04	Yellow	1	1
Memory	CXK77B3641A33	BICMOS	2.5	No	03/12/98	1.33	Yellow	1	1
Memory	TC40H194F	CMOS	5	No	01/01/85	14.53	Red	0	0
Memory	5074J883C	TTL	5	Yes	01/01/78	21.53	Red	0	0
Memory	LH531024U	CMOS	5	No	01/01/97	2.52	Green	1	2
Memory	TC514266AZ70	CMOS	5	No	03/01/91	8.36	Green	1	2
Memory	M38510R24506BVX	CMOS	5	Yes	06/15/90	9.07	Yellow	1	1
Memory	LC372200PM10	CMOS	5	No	09/01/95	3.86	Red	0	0
Memory	CAT24C082JA25	CMOS	3	No	11/01/97	1.69	Yellow	1	1
Memory	M27V101-100FI	CMOS	3.3	No	10/01/90	8.78	Yellow	1	1
Memory	AT29BV040A25TI	CMOS	3	No	02/01/93	6.44	Yellow	1	1
Memory	DM7590W/883	TTL	5	Yes	01/01/89	10.53	Red	0	0
Memory	IBM13N3649JC10T	CMOS	3.3	No	01/01/97	2.52	Green	1	2
Memory	HY88321QF15	CMOS	3.3	No	10/01/95	3.78	Yellow	1	1
Memory	HN624032FB15	CMOS	5	No	05/01/92	7.19	Red	0	0
Memory	MK45180Q20	CMOS	5	No	10/01/92	6.78	Yellow	1	1
Memory	MSM51257-85RS	CMOS	5	No	01/01/92	7.53	Yellow	1	1
Memory	57C4502J883B	CMOS	5	Yes	04/01/86	13.28	Red	0	0
Memory	N74198F	TTL	5	No	05/01/78	21.21	Yellow	1	1
Memory	SN74ACT2154	CMOS	5	No	06/01/90	9.11	Yellow	1	1
Memory	KMM5324000BKG5	CMOS	5	No	01/01/94	5.52	Yellow	1	1
Memory	5962-9232103MXX	CMOS	5	Yes	03/26/93	6.29	Yellow	1	1
Memory	8413205YA	CMOS	5	Yes	09/13/88	10.83	Green	1	2
Memory	6381-IN	TTL	5	No	01/01/78	21.53	Red	0	0
Memory	MSC2350-10YS12	CMOS	5	No	01/01/90	9.53	Red	0	0
Memory	IMS1203P35	CMOS	5	No	02/01/89	10.44	Red	0	0
Memory	MAL9287FBBAF	CMOS	5	Yes	01/01/91	8.53	Red	0	0
Memory	MR27V802D-RS	CMOS	3	No	07/01/93	6.03	Yellow	1	1
Converter	SC12482CV66	CMOS	5	No	01/01/92	7.53	Red	0	0
Converter	5962-9305709MPX	CMOS	5	Yes	07/19/94	4.98	Yellow	1	1
Converter	RGBDAC3800/M	Hybrid	5	No	01/01/86	13.53	Red	0	0
Converter	ADC80MAH12BI	Hybrid	5	No	01/01/89	10.53	Yellow	1	1
Converter	AD1678JD	BICMOS	5	No	07/01/89	10.03	Red	0	0
Converter	AD579TD/883D	Hybrid	5	Yes	01/01/92	7.53	Yellow	1	1
Converter	5962-9176403MXX	BICMOS	5	Yes	05/20/93	6.14	Yellow	1	1
Converter	SDC14620-112	Hybrid	5	Yes	01/01/92	7.53	Yellow	1	1
Converter	TLC5618IP	CMOS	5	No	07/01/97	2.02	Yellow	1	1
Ind Control	DS1815R20	CMOS	1.2	No	02/26/98	1.37	Yellow	1	1
Industrial Control	AN6386K	Bipolar	5	No	04/01/88	11.28	Red	0	0
Ind Control	TA7768F	Bipolar	3	No	03/01/90	9.36	Red	0	0
Interface	EL7144CS	CMOS	15	No	01/01/94	5.52	Red	0	0

Function	Part #	Technology	Voltage	Military	Data-sheet Date	Design Age (as of 7/10/99)	Generic flag	DMSMS	DMSMS Trilevel
Interface	SN74120	TTL	5	No	04/01/88	11.28	Green	1	2
Interface	SNM55142J	Bipolar	5	Yes	01/01/77	22.53	Red	0	0
Interface	VSC7923KF	GAAS	5.2	No	03/23/98	1.30	Yellow	1	1
Interface	UCC5610J	BICMOS	3	No	01/01/95	4.52	Yellow	1	1
Interface	AD8108AST	Bipolar	5	No	10/01/97	1.77	Red	0	0
Interface	5962-8944706HXA	Hybrid	5	Yes	04/08/94	5.26	Yellow	1	1
Interface	KT8593N	CMOS	14	No	06/01/92	7.11	Red	0	0
Interface	T6B07	CMOS	3	No	04/07/97	2.26	Yellow	1	1
Interface	CGS74CT2525N	CMOS	5	No	07/01/91	8.03	Green	1	2
Interface	CGS54CT2526E	CMOS	5	No	01/01/92	7.53	Red	0	0
Peripheral	UPD72120L	CMOS	5	No	08/01/88	10.95	Yellow	1	1
Peripheral	UPD71641R	CMOS		No	01/01/91	8.53	Yellow	1	1
Peripheral	MPC973FA	CMOS	3.3	No	09/01/94	4.86	Yellow	1	1
Peripheral	LH0081AU	MOS	5	No	10/01/90	8.78	Red	0	0
Peripheral	DS1685S3	CMOS	3	No	01/01/95	4.52	Yellow	1	1
Peripheral	TDA5155X	BICMOS	5	No	04/08/97	2.25	Red	0	0
Peripheral	HT6513B	CMOS	5	No	10/23/96	2.71	Yellow	1	1
Peripheral	AV9103-01CN8	CMOS	5	No	10/01/91	7.78	Red	0	0

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Vita

First Lieutenant Michael James Gravier was born on 3 February 1971 in Fort Lewis, Washington. After graduating from Clover Park High School in June of 1989, he entered undergraduate studies at Washington University in St. Louis, Missouri. He spent a year in graduate level studies in the University of Salamanca, Spain, studying medieval Spanish philology and archaeology. In June of 1993 he graduated with a Bachelor of Arts with honors from Washington University with a double major in physical anthropology and Spanish literature.

After graduating from OTS in November of 1995, 1Lt. Gravier was assigned to Mountain Home AFB, Idaho. There he served as vehicle operations flight commander and traffic management flight commander, as well as filling the shoes of the transportation control officer for every major deployment from Mountain Home AFB from December 1995 through April 1998. In May 1998, he entered the Graduate Logistics Management with a specialty in Transportation program, School of Logistics and Acquisition management, Air Force Institute of Technology. Upon graduation, he will be assigned to the 3d Aerial Port Squadron, Pope AFB, North Carolina.

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13. ABSTRACT *(Maximum 200 words)*

The problem of Diminishing Manufacturing Sources and Material Shortages (DMSMS) afflicts the Air Force and other armed services in a way unforeseen in the past. The costs of DMSMS manifest themselves both in terms of monetary expense and diminished mission readiness. The current environment of limited defense spending and high operations tempo exacerbates this problem. This thesis draws on available data from the electronics integrated circuit industry to attempt to assess whether statistical modeling offers a viable method for predicting the presence of DMSMS. The research identified logistic regression as a powerful tool for analysis of DMSMS and further developed twenty models attempting to identify the "best" way to model and predict DMSMS using logistic regression. The results indicated that DMSMS does not seem related to technical characteristics. However, design age proved to be statistically significant in modeling DMSMS presence. Another finding of this research indicates that integrated circuits designed for military use have extended longevity compared to commercial integrated circuits.

The overall conclusion of this effort was that DMSMS can be predicted using the conditional probability output of logistic regression. Current databases do not provide easy access to the vital predictor, design age. Recommendations include further validation of the model and the inclusion of design age in electronics integrated circuit databases.

14. SUBJECT TERMS
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